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

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Abstract

US multinationals formed joint ventures in China for market access and lower labor costs. However, these ventures transfer technology to Chinese firms, fueling future competition. While individual firms weigh the risks to their own profits, they disregard the negative impact on other US firms and the broader economy, resulting in an overinvestment that may reduce US welfare. In our empirical analysis, industries with more joint ventures in China show positive spillovers to Chinese firms but negative outcomes for firms in the US. We develop a two-country model with oligopolistic competition, innovation, and joint ventures. For the US, the short-run gains from joint ventures are outweighed by long-run losses due to rising Chinese competition. Joint ventures benefit large US firms at the expense of small firms and the real wages of workers. A ban on joint ventures since 1999 would have boosted US welfare by 1.2 percent.

Keywords: Technology transfer, technology diffusion, innovation, competition, joint venture, foreign direct investment
JEL Codes: F23, O25, O33

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1. Introduction

Intensifying economic rivalry between the United States (US) and China has heightened scrutiny of China's economic policies and business practices. For instance, China has long mandated that multinational enterprises (MNEs) transfer technology as a condition for market access. This often involved the formation of joint ventures, as such arrangements were considered more conducive to technology transfer than other forms of foreign direct investment (FDI). This practice has been criticized by some as a form of intellectual property "theft" and has also been cited as a factor exacerbating the trade imbalance between the US and China. In light of these concerns, the US has imposed restrictions on outward FDI in critical technologies.[1]

However, US firms opted to form joint ventures with Chinese partners voluntarily to gain access to the Chinese market and cheaper labor, even with the risk of technology leakage. This raises a crucial question: What is the economic justification for government intervention when MNEs voluntarily engage in such partnerships? US firms recognize that by establishing joint ventures, they will facilitate technology diffusion that enhances the productivity of their Chinese partners and other local firms, thereby intensifying global competition. However, they do not care about the profit losses that other US firms will suffer from intensified global competition. This may lead to an over-investment in joint ventures and excessive technology transfer to China from the perspective of what is socially optimal for the US. Despite this seemingly straightforward economic logic, this specific mechanism has not been formally explored in the literature. This gap presents a significant opportunity to provide novel insights.[2]

Our paper makes two primary contributions. First, we provide empirical evidence of the technology diffusion and competition effects of joint ventures into China. A novel finding is

[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 . . . [F]oreign 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 CHIPS and Science Act of 2022 prohibits US government funding recipients from making certain investments in China.

[2] On FDI and technology transfer to China, a former Tesla executive said: "In this game, one American company gets to win. They don't care if all their US competitors lose. It's actually better for them. But on the other side, all the Chinese companies win. They all get to step up and create a massive market where none previously existed." McGee (2025, p.283)

that US firms in industries with greater joint venture activity in China experienced more pronounced negative outcomes. Second, we develop a two-country endogenous growth model where oligopolistic firms strategically determine their innovation and joint venture decisions, and we analyze the full dynamics of the model. Our quantitative analysis demonstrates that, from a US social welfare perspective, the market equilibrium leads to an excessive number of joint ventures.

For our empirical analysis, we constructed a dataset by integrating firm-level balance sheet data from China's National Bureau of Statistics, patent data, and ownership structure information from the Orbis database. Data for US firms were sourced from Compustat. This combined dataset allows us to document three key empirical findings.

First, we find *direct* positive spillovers from MNEs to their Chinese joint venture partners. Using an event study design, we matched Chinese parent firms that established joint ventures with MNEs (the treated group) with a control group of firms that never formed such relationships, using propensity score matching.[3] Following the formation of these joint ventures, the Chinese parent firms experienced significant growth in sales, capital, and exports. Furthermore, their patenting activities became more similar to those of their MNE partners, indicating a direct diffusion of technology between partners.

Second, we find evidence of *indirect* spillovers to other Chinese firms. In industries with higher levels of joint ventures, even Chinese firms that were not part of a joint venture grew faster and became more technologically advanced.

Third, and most importantly, we find that in industries with greater joint ventures into China, US firms experienced more negative outcomes in terms of sales, employment, investment, and innovation. We provide both correlational and instrumental variable (IV)-based evidence for these findings. We do not find such negative outcomes for wholly foreign-owned enterprises—an FDI arrangement that, unlike joint ventures, does not involve local partners.

For the quantitative analysis, we develop a two-country model with endogenous technological change, where oligopolistic firms make strategic decisions on innovation and joint ventures. In each industry, the market structure consists of a leader and a fringe firm in each

[3]Using propensity score reweighting on Spanish firms, Guadalupe et al. (2012) document positive selection of local firms into being acquired by foreign MNEs and find that, after acquisition, these firms invest more in innovation and reach larger markets through their foreign parents.

country. All firms produce differentiated varieties, which they sell in both their domestic and foreign markets. While firms possess market power within their specific industry, the economy features a continuum of industries, ensuring that no single firm can influence aggregate prices or quantities. Leaders can enhance their productivity through innovation. In addition, US leaders have the option to establish joint ventures in China, partnering with their Chinese counterpart in the same industry. These ventures enable US firms to bypass trade costs and utilize lower-cost Chinese labor for production. The surplus generated from these joint ventures is then divided between the two leader firms via Nash bargaining.

Even without joint ventures, the model allows for the stochastic diffusion of technology both within and between countries, acknowledging that joint ventures are not the sole channel of technology transfer. The establishment of a joint venture in China increases the probability of technology diffusion from the US leader firm to its Chinese counterpart, a feature consistent with our empirical finding of direct spillovers. Consequently, the surplus from a joint venture includes not only the flow profit of the venture but also the value derived from the increased probability of technology diffusion to the Chinese leader firm. Additionally, Chinese fringe firms, which are not involved in any joint ventures by design, benefit indirectly. This is because the joint venture firm itself represents an additional source of technology diffusion within the industry, and the Chinese leader firm is likely to achieve higher productivity after forming the joint venture. This mechanism aligns with our empirical finding of indirect spillovers.

The entry of a new joint venture firm immediately intensifies competition within the industry. The ongoing stochastic diffusion of technology to Chinese leader and fringe firms intensifies this competitive pressure over time. The US leader takes these competition effects into account when deciding whether to form a joint venture. It also captures a portion of the joint venture's profit flow and the spillover benefits to the Chinese leader through the bargaining process. However, the US leader does not account for the negative competition effects on its domestic competitor, the US fringe firm. Our third empirical finding serves as a manifestation of this negative competition effect.

We solve for the model's transitional dynamics, tracing the economy from an initial state where Chinese firms have lower productivity than their US counterparts, toward a balanced growth path. We calibrate the model to match key empirical moments observed along this

transition path. Notably, we infer the parameters governing technology diffusion directly from the regression coefficients presented 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 reduced labor costs. They also partially capture the value of technology transfer to Chinese leader firms via bargaining. Over time, however, Chinese firms catch up faster due to the technology diffusion facilitated by these joint ventures, and the heightened competition negatively affects US leaders' long-run profits. Nonetheless, the present discounted value of US leaders' profits is higher with joint ventures—otherwise, they would not choose to invest in them. For US fringe firms, the joint ventures of leader firms have a purely negative effect on their profits through intensified competition from China. Because US leader firms do not internalize this negative effect on their domestic competitors, there may be an excessive number of joint ventures relative to the US social optimum. This result crucially depends on the assumption that fringe firms produce positive quantities in equilibrium. If we were to follow the common assumption in the literature that fringe firms only pin down limit pricing but do not produce, US leaders would take into account the full negative effect of joint ventures on the industry. This would make it unclear whether an over-investment in joint ventures in China would occur.

Joint ventures shape US leaders' innovation through three forces. The option-value and market-size effects raise innovation when JVs are available: innovation increases the total JV surplus US leaders capture through bargaining, and JVs enlarge the effective market and raise marginal returns to R&D. The leakage effect works in the opposite direction: by accelerating technology diffusion to Chinese rivals, JVs erode future profits and reduce the return to innovation. In our quantitative analysis, the leakage effect dominates in the medium to long run, leading US leaders to innovate less when presented with the joint venture option. For Chinese leaders, technology diffusion serves as a substitute for their own innovation efforts, so they also innovate less when a joint venture is established.

Furthermore, in our model, the value and, consequently, the likelihood of a US leader forming a joint venture are greater when the US-China technology gap is wider. This theoretical prediction is confirmed by our empirical data. Because joint ventures reduce the technology gap between US and Chinese firms through technology diffusion, they have the effect of eroding the US's comparative advantage and worsening its terms of trade, thereby

reducing the gains from trade for the US.

These effects on innovation and comparative advantage help us understand the general equilibrium implications of joint ventures, which individual firms, by their nature, ignore. As US leaders shift a portion of their production to China, the reduced domestic labor demand leads to lower wages in the United States. Although joint ventures and the technology diffusion they engender do reduce the price of goods, this reduction is not sufficient to prevent a decline in the real wage. Two key reasons for this outcome are the reduced innovation and the diminished gains from trade discussed above. A final contributing factor is that joint venture decisions are driven not only by production cost savings but also by the fees US leaders collect from the stochastic transfer of technology.

To compute the welfare consequences of joint ventures, we analyze the effect of a policy that prohibits US firms from forming joint ventures with Chinese firms, effective from 1999—the start of our dataset. We find that this prohibition 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 rise by 4.9 percent. Although the total profit of the corporate sector declines, the real wage increases by 2.9 percent due to higher labor demand in the US, which drives the overall welfare gain. The ban has a transitory negative effect, as US firms can no longer immediately benefit from lower wages and reduced trade costs in China. However, this effect is outweighed by medium-run benefits, as the United States maintains its technological advantage over China for longer, driven by less technology leakage and higher innovation efforts.

When the US prohibits joint ventures, Chinese leader firms compensate for the reduced technology diffusion by increasing their own innovation efforts. However, this policy substantially delays China's productivity growth and reduces China's welfare by 10.3 percent in units of permanent consumption. In China, the profits of both leaders and fringe firms, as well as the real wage, are all lower without joint ventures from the United States.

In an effort to isolate the source of over-investment in joint ventures, we consider an alternative scenario in which US leader firms are required to compensate fringe firms for losses incurred due to joint ventures. That is, US leaders are compelled to internalize the negative effects of joint ventures on the profits of their domestic competitors. With such multilateral bargaining, significantly fewer joint ventures are formed. Moreover, in this setting, a com-

plete ban on joint ventures actually decreases US welfare. This indicates that the failure to account for the profit losses of other US firms is a key source of the market inefficiency, and that coordinated joint venture decisions can deliver a higher welfare level for the US than an outright ban would.

We evaluate how China's elimination of the quid-pro-quo policy affects US and Chinese welfare. In the model, direct diffusion is the counterpart of the quid-pro-quo policy. Shutting down this channel raises US welfare by 3.2 percent and reduces Chinese welfare by 5.3 percent relative to the baseline with the direct diffusion channel.

In fact, our result does not imply that prohibiting joint ventures would *always* be welfare-enhancing for the US. If new joint ventures were prohibited starting in 2025, a time when the US-China technology gap is significantly smaller than in 1999, the competitive effects from direct and indirect spillovers would be less pronounced. This would reduce the market inefficiency associated with joint ventures. In this specific scenario, the loss of short-run gains from joint ventures is relatively large, and the medium-run boost to innovation efforts is sufficiently small that a policy of banning joint ventures would, in fact, reduce US welfare.

We also consider China's retaliation against the US JV ban through labor subsidies and compute the Nash equilibrium of the two countries' policy responses. In this case, the US still bans JVs but welfare gains from the ban decrease from 1.2 percent to 0.22 percent due to China's retaliation through 20 percent subsidy. With policy cooperation, however, the optimal outcome is for the US not to ban JVs and for China to make transfers to the US to share the global gains, which can increase both countries' welfare by 5.7 percent. We also show that even without modeling China's retaliation or policy cooperation, the US government does not ban JVs when its objective function has a higher discount rate or places weight on leaders' profits.

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; Arkolakis et al., 2020; Buera and Oberfield, 2020; Perla et al., 2021; Sui, 2025; Cai et al., 2022; Peters, 2022; Bai et al., 2025b,c; de Souza et al., 2025; Hémous, David and Ossa, Ralph, and Lepot, Simon and Sampson, Thomas and Schärer, Julian, 2025; Milicevic et al., 2025; Santacreu, 2025). 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). Akcigit et al. (2024) discuss technology leakages in the context of Chinese venture capital investment in the US and national security concerns. Lai (1998) and Branstetter and Saggi (2011) study intellectual property rights using models where imitation, innovation, and FDI are jointly determined. Lam (2024) focuses on technology leakage to China through illegal imitation and studies optimal intellectual property rights protection. Our contribution lies in studying the negative competition effects of joint ventures through technology leakages and quantitatively analyzing the policy implications.[4]

Holmes et al. (2015) study the welfare implications of China's quid pro quo policy in a multi-country dynamic general equilibrium model with technology-capital transfers developed by McGrattan and Prescott (2009). Their technology capital is analogous to innovation in our model. Our conclusions go in the similar direction as theirs: technology leakage to China lowers multinationals' incentives to form joint ventures, dampens US innovation, and reduces US welfare. We differ in three respects. First, our model focuses on a negative externality among US firms due to strategic interaction: leader firms do not internalize the profit loss their joint ventures inflict on US fringe firms. We find that once this externality is corrected for, fewer joint ventures are established and the US can derive positive welfare from joint ventures even under the quid pro quo. Second, we show that joint venture decisions interact with comparative advantage and innovation. Third, our model is calibrated on firm-level microdata and our reduced-form estimates.

Second, this paper also contributes to the quantitative trade literature on multinationals (e.g., Irarrazabal et al., 2013; Keller and Yeaple, 2013; Antràs et al., 2017; Arkolakis et al., 2018; Cravino and Levchenko, 2017; Boehm et al., 2019; Head and Mayer, 2019; Bilir and Morales, 2020; Wang, 2021; Alviarez et al., 2023; Garetto et al., 2024; Fan, 2025; Cai and Xiang, 2025). Our model focuses on the interaction between two countries, but it preserves key ingredients

[4]Regarding China's growth, Song et al. (2011) study reallocation from less-productive state-owned to more-productive private firms under financial frictions during China's economic transition; Alder et al. (2016) study place-based policy; and König et al. (2022) examine the dynamic effects of misallocation on China's TFP growth. We identify joint ventures as a key learning channel.

of multinational production such as proximity-concentration trade-offs (Helpman et al., 2004) and export platforms (Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017). Among recent papers on US-China technology rivalry (e.g., Ju et al., 2024; Ma et al., 2025a,b), Ma and Zhang (2025) is closest: they document positive FDI spillovers from Chinese patent data and find, in a Ricardian trade–multinationals–innovation model, that the quid pro quo policy substantially raised China's welfare—consistent with our China-side results. Our contribution is on the US side and highlights the dynamic trade-off between market access and technology leakages for MNEs.

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 Bai et al. (2025a) and Jiang et al. (2024). Our finding of indirect spillovers to Chinese firms that do not participate in joint ventures is in line with previous papers that document positive spillovers from foreign MNEs to domestic firms in host countries.[5] In addition to these findings, we provide evidence on negative competition effects of joint ventures on other US firms.[6] That we find negative effects for joint ventures but not for wholly foreign-owned enterprises shows that the mode of FDI matters for these negative outcomes.[7]

Finally, this paper relates to the literature on the China shock and the decline of the US manufacturing sector (Autor et al., 2013). Our empirical results show that, as joint ventures flowed into China, Chinese firms became more competitive in the global market and US manufacturing firms experienced negative outcomes in sales, employment, and innovation.[8]

[5]For example, see Javorcik (2004); Javorcik and Spatareanu (2008); Guadalupe et al. (2012); Wang and Wang (2015); Lu et al. (2017); Alfaro and Chen (2018); Bilir and Morales (2020); Setzler and Tintelnot (2021); Alfaro-Ureña et al. (2022) for direct and indirect spillovers from FDI.

[6]This differs from the negative competition effects of MNEs' entry on firms in host countries documented in Aitken and Harrison (1999) and Bao and Chen (2018).

[7]See Nocke and Yeaple (2007) for theoretical perspectives on modes of FDI; Javorcik and Spatareanu (2008) find stronger spillovers with greater local participation among Romanian firms.

[8]Evidence on the China shock's effect on firm innovation is mixed. Bloom et al. (2016) find positive impacts on European firms, whereas Autor et al. (2020) find negative impacts on US firms. Aghion et al. (2024) find that the output shock decreased French firms' innovation, while the input-supply shock had positive impacts.

2. Background and Data

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

After decades of isolation, Deng Xiaoping initiated economic reforms and opened China to foreign investment in 1979 with the "Law on Sino-Foreign Equity Joint Ventures" (henceforth referred to 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 in exchange for access to China's large consumer market and abundant labor. From 1979 to 1986, JVs were the only legally permitted form of FDI in China, and WFOEs were gradually allowed in some sectors starting in 1986. Following China's WTO accession in 2001, the Chinese government introduced a major FDI policy reform, 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.[9]

[9] In its 2017–18 Section 301 investigations, the Office of the United States Trade Representative reported that China implicitly pressured foreign MNEs to form JVs and transfer advanced technologies through both formal regulations and informal administrative barriers. Holmes et al. (2015) also showed that the mandates became implicit but remained in effect. Some described it as "voluntary is the new mandatory" (McGee, 2025).

2.2 Data

We construct our main dataset by merging balance sheet, ownership structure, and patent data for Chinese and US manufacturing firms, along with sector-level data, over 1998–2013. All monetary values are in 2007 US dollars. Appendix A provides more details.

We obtain the Chinese firm balance sheets from the Annual Survey of Industrial Enterprises, constructed by the National Bureau of Statistics. We have annual data on firm sales, exports, employment, and capital (measured as fixed assets), their affiliated 4-digit 1994 Chinese Industry Classification (CIC) codes, and location for all state-owned and private firms with sales exceeding 5 million Renminbi (RMB) before 2010 and 20 million RMB since 2011. To ensure consistency, we apply the 20 million RMB threshold throughout the sample period. The data are 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 MNEs from Hong Kong, Macao, and Taiwan, given the special economic and regulatory relations between mainland China and these regions. We also use 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 outcomes 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.[10] A firm's industry classification follows 4-digit 1987 SIC codes. We aggregate these codes up to 383 4-digit codes for compatibility with the CIC and HS codes.[11]

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 the Orbis Global database. We clean the data following Kalemli-Ozcan et al. (2024). We match

[10] According to SFAS No. 131, US publicly-listed firms need to disclose foreign sales when they account for more than 10% of total sales, which is the source of information in the historical segment data.

[11] We follow Autor et al. (2013) and aggregate 4-digit SIC codes into 387 industries, then further consolidate these to 383 industries for compatibility with CIC and HS codes. We map CIC codes to SIC codes using the concordance from Ma et al. (2014).

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). From CNIPA's three patent types (innovation, utility model, and design), we include only innovation patents; from USPTO, we include only utility patents, which are analogous to CNIPA's 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 (IPC) codes. When constructing patent stock, we use a depreciation rate of 0.30 following Li and Hall (2020).[12]

We obtain sector-level manufacturing data from the US NBER-CES Manufacturing Industry Database and China's National Bureau of Statistics, and bilateral trade data from UN Comtrade.

3. Motivating Facts

In this section, we present three motivating facts on joint ventures.

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

[12]Specifically, we compute $F_{it} = \text{NewPatent}_{it} + 0.7 \cdot F_{i,t-1}$, where F_{it} is firm i's vector of patent stocks and NewPatent_{it} is the vector of new patents across technological fields. Total patent stock is the sum across all IPC codes.

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 yields 176 matches, involving 176 unique treated firms and 692 unique control firms. The matched treated and control groups are well-balanced across observables, including various size measures, labor productivity, patenting activity, and export status (Appendix Table B1). A balance test—regressing the treatment dummy on these pre-event observables—confirms that none of these observables significantly predicts treatment status (Appendix Table B2).

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

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

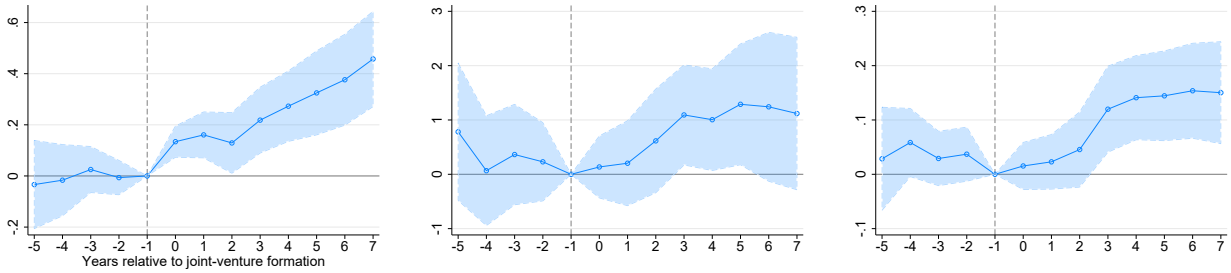
where i denotes firm, m match, and t year. D_{mt}^{τ} are event-time dummies defined as $D_{mt}^{\tau} \equiv \mathbb{1}[t - t(m) = \tau]$, where $t(m)$ is the event year of match m. $\mathbb{1}[\text{JV Partner}_i]$ is an indicator for treated (JV-forming) firms after the event. We normalize $\beta_{-1} = 0$. δ_{im} and δ_{mt} are match-firm and match-year fixed effects.[13] ε_{imt} is the error term. Standard errors are two-way clustered at the match and firm levels to account for mechanical correlations introduced by matching with replacement, since the same firm may appear in multiple matches.

We consider three dependent variables: log sales, inverse hyperbolic sine transformation of exports, and a measure of technological proximity to foreign MNE partners. The first two 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 partners after forming JVs. If Chinese firms acquired technology from foreign MNEs through joint ventures, we would expect an increase in their technological similarity to these foreign partners over time.

Following Jaffe (1986) and Bloom et al. (2013), we calculate technological proximity based

[13] This is a fully-stacked event-study design that does not suffer from the complications raised in the recent staggered DiD literature (Roth et al., 2023).

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



A. Log sales B. Ihs exports C. Technological proximity

Notes: This figure illustrates the event study estimation results of equation (3.1). 95% confidence intervals are based on standard errors two-way clustered at the match and firm levels. β_{-1} is normalized to zero.

on cosine similarity using patent data, as patents reflect their technological capabilities:[14]

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

$F_{imt} = (p_{i1t}, \ldots, p_{iKt})$ 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. 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. 1-3 of Appendix Table B3 for more details). Four years after forming JVs for the first time, Chinese partners' sales increased by 27%, with improvements in export performance. Furthermore, they became closer to their foreign MNE counterparts technologically. These findings suggest that their improved performance is related to technology transfer and diffusion from foreign MNE partners. Forming JVs also

[14]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 in the Chinese patent system and foreign MNEs to those who ever patented at USPTO.

had positive impacts on log capital, log employment, export dummies, cumulative patents and yearly new patents (see Appendix Table B3).

The event-study coefficients identify relative effects between the treated and control groups. If newly formed JVs took sales from control-group firms operating in the same sector, the post-event coefficients would capture not only the treated firms' gains but also the offsetting decline in control-firm sales through this competition effect.[15] Appendix Figure B1 shows that this is not the case: control-group sales follow the same trend before and after the event, while only treated-group sales rise, ruling out this alternative explanation.

The results are robust to alternative numbers of matches and depreciation rates for patent stock used for construction of the technological proximity measure (Appendix Table B4). Because matching is based on observables, time-varying unobservables may threaten the parallel-trends assumption. Following the sensitivity analysis of Rambachan and Roth (2023), our results are robust to mild violations of parallel trends (Appendix Figure B2).

Fact 2. Indirect Positive Spillovers to Chinese Firms

Next, we present suggestive evidence that JVs also benefited Chinese firms not directly involved in JVs. We consider the following long-difference specification over 1999–2012:

$$\Delta y_{fj} = \beta_1 \Delta \text{JV}_{fj} + \beta_2 \Delta \text{WFOE}_{fj} + \vartheta \text{NTRgap}_j + \mathbf{X}'_{fj}\gamma + \varepsilon_{fj}, \tag{3.3}$$

where f indexes firms and j indexes 4-digit industry codes. The dependent variable Δy_{fj} is the DHS growth rate (Davis et al., 1998) of firm-level outcomes, $100 \times \frac{y_{fj,12} - y_{fj,99}}{0.5(y_{fj,12} + y_{fj,99})}$. $\mathbf{X}_{fj}$ is a vector of additional firm- or industry-level controls. We include dummies for state-owned firms in all specifications. ε_{fj} is the error term. Regressions are weighted by firms' initial sales, and standard errors are clustered at the CIC 3-digit level.

ΔJV_{fj} measures industry-level JV exposure in China, defined as the change in total domestic sales of JV affiliates from MNEs of all source countries in industry j over 1999–2012,

[15] This would violate the Stable Unit Treatment Value Assumption (SUTVA).

normalized by total industry j sales in 1998[16]:

$$\Delta \text{JV}_{fj} = \frac{\Delta \text{JV dom. sales}_{fj}}{\text{Total sales}_{j,98}} = \frac{\sum_{g \in \mathcal{J}_{(-f)j,12}} \text{Sales}^{\text{dom}}_{gj,12} - \sum_{g \in \mathcal{J}_{(-f)j,99}} \text{Sales}^{\text{dom}}_{gj,99}}{\text{Total sales}_{j,98}}, \tag{3.4}$$

where $\mathcal{J}_{(-f)j,t}$ is the set of JV affiliates in industry j in year t, excluding affiliates of f. In the numerator, we use domestic sales rather than total sales because many JV affiliates in China engage in processing trade—serving export markets without complex manufacturing activity—which is unlikely to generate technology diffusion.[17] We include JV affiliates from MNEs of all source countries because positive spillovers may arise not only from US MNEs but also from MNEs of other countries. Finally, we exclude f's own JV affiliates from the numerator (denoted $-f$) to rule out mechanical correlations.

We also include the sectoral WFOE exposure ΔWFOE_{fj}. Including this measure lets us compare how JVs and WFOEs differ in their effects on Chinese firms; it also ensures that the coefficient on ΔJV_{fj} captures the JV-specific channel rather than broader FDI effects. ΔWFOE_{fj} is defined analogously to JV exposure:

$$\Delta \text{WFOE}_{fj} = \frac{\Delta \text{WFOE dom. sales}_{fj}}{\text{Total sales}_{j,98}} = \frac{\sum_{g \in \mathcal{W}_{(-f)j,12}} \text{Sales}^{\text{dom}}_{gj,12} - \sum_{g \in \mathcal{W}_{(-f)j,99}} \text{Sales}^{\text{dom}}_{gj,99}}{\text{Total sales}_{j,98}}, \tag{3.5}$$

where $\mathcal{W}_{(-f)j,t}$ is the set of WFOE affiliates in industry j in year t, excluding affiliates of f. We restrict the sample to Chinese firms that are neither JV nor WFOE affiliates, since JV and WFOE affiliates are used to construct the exposures.

To isolate the role of JV exposure from changes in post-WTO trade policy, we include NTRgap_j, which measures reductions in US-China trade-policy uncertainty at the industry level following the granting of Permanent Normal Trade Relations (PNTR) to China and is correlated with the decline in US manufacturing (Pierce and Schott, 2016).[18]

[16] This is a standard industry-level FDI exposure measure in the literature (e.g., Aitken and Harrison, 1999; Lu et al., 2017; Jiang et al., 2024). A concordance issue arises because a single 4-digit CIC code often maps to multiple 4-digit SIC codes. We first construct the industry-level shock at the 4-digit SIC level (since most data are in SIC codes), then take a weighted average across SIC codes mapped to each 4-digit CIC code. Appendix B.1 provides further details.

[17] Defever and Riaño (2012), Yu (2015), and Manova and Yu (2016) document the prevalence of processing trade among Chinese exporters and FDI affiliates. We later show that our results remain robust to using total sales in the numerator.

[18] NTRgap_j is the potential increase in US tariffs on Chinese goods had Congress failed to renew China's

Table 1: Indirect Positive Spillovers to Chinese Firms (OLS)

Dep. var.	ΔSales		ΔEmp.		ΔCapital		ΔExport		ΔPatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ΔJV_{fj}	7.71***	5.36***	4.04***	3.48**	4.99***	2.88**	21.35***	18.49***	1.79	1.82*
	(1.65)	(1.64)	(1.46)	(1.68)	(1.32)	(1.37)	(3.56)	(2.82)	(1.27)	(1.04)
$\Delta WFOE_{fj}$	2.58	9.13	8.15	10.18*	9.06	10.87*	29.40*	13.30	0.39	−0.92
	(4.69)	(6.18)	(5.82)	(5.79)	(5.59)	(6.37)	(15.09)	(12.01)	(2.36)	(2.10)
$NTRgap_j$	−0.08	0.13	0.64**	0.60**	0.09	0.10	1.23	1.16	0.27	0.34
	(0.38)	(0.39)	(0.28)	(0.30)	(0.29)	(0.28)	(0.78)	(0.79)	(0.30)	(0.30)
Add. ctrl.		✓		✓		✓		✓		✓
Mean dep. var.	81.74	81.74	−18.92	−18.92	45.59	45.59	49.74	49.74	186.58	186.58
# clusters	156	156	156	156	156	156	154	154	154	154
N	11978	11978	11978	11978	11978	11978	6137	6137	5270	5270

Notes: Standard errors, clustered at the CIC 3-digit level, are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports OLS estimates of equation (3.3). ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). The dependent variables in columns 1–2, 3–4, 5–6, 7–8, and 9–10 are the DHS growth rates of sales, employment, capital, exports, and cumulative patents over 1999–2012. The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. All specifications include dummies for state-owned firms. The even columns add US sectoral employment and value-added growth (1993–1998), 1996 US import penetration, 1993 US production worker shares, 1990 US computer and high-tech investment shares, and 1-digit industry dummies. All regressions are weighted by initial sales.

Table 1 presents the results. In column 1, the dependent variable is sales growth, and the OLS estimate on JV exposure is positive and statistically significant at the 1% level. A 1 percentage point increase in JV exposure in industry j is associated with a 0.08 percentage point higher sales growth rate for Chinese firms in that industry. If these positive spillovers were driven by systematic decline of advanced-economy sectors that were outsourced to China, our coefficient would reflect a spurious correlation. To probe this, in column 2 we add controls for industry-level technological trends and pretrend variables (US sectoral growth in employment and value-added over 1993–1998).[19] The coefficient is not sensitive to these additional controls and remains stable, within one standard error of the baseline estimate. In columns 3–10, JV exposure is positively correlated with growth in employment, capital, exports, and cumulative patents.[20]

Normal Trade Relations (NTR) status annually prior to the granting of PNTR.

[19]The industry-level technological-trend controls are 1996 US import penetration, 1993 production worker shares, 1990 computer and high-tech investment shares, and 1-digit industry dummies.

[20]The sample size decreases for export and patent outcomes because DHS growth is well-defined only when the outcome takes a non-zero value at the start or end of the sample.

Only JV exposure is statistically significant, while WFOE effects are less precisely estimated. This is consistent with stronger diffusion through JVs, since JVs involve closer engagement between local firms and MNEs, which is absent for WFOEs. The NTR gap has positive effects on Chinese firms, although these estimates are less precise.

We further provide evidence of productivity (or quality) improvements in Chinese firms. JV exposure is positively correlated with various productivity proxies, including DHS growth in the number of exported products and destination countries over 2000–2013 (from Chinese customs data), wage growth (a proxy for worker skill), and indicators for receiving a "high-tech" certificate from the government (Appendix Table B5). WFOE exposure shows no such positive and significant relationships.

In Appendix B.3, we provide additional evidence supporting technology diffusion using patent citation flows, where citation is used as a proxy for idea flows (Jaffe et al., 1993). We find that foreign MNEs that formed JVs began to receive more citations from non-partner Chinese firms, compared to observationally similar MNEs that did not form any JVs with Chinese partners (Appendix Figure B3).

There are several potential channels behind these indirect spillovers. First, the results may reflect technology diffusion through worker mobility from MNEs to other firms (e.g., Poole, 2013). Second, FDI affiliates are likely to generate greater demand and lower supply costs for other Chinese firms (e.g., Alfaro-Ureña et al., 2022), thus providing stronger incentives for quality and productivity upgrading. Gong (2023) also finds similar positive indirect spillovers of FDI in China, and Setzler and Tintelnot (2021) find them for the US.

Fact 3. Negative Outcomes for US Firms

We examine how the rise in JV activity in China affects US firms. We re-estimate the OLS long-difference regression in equation (3.3) over 1999–2012 for US firms, excluding any MNE that established a JV or WFOE affiliate in China during the sample.[21] This sample restriction isolates the negative effect on US firms that did not themselves invest in China, separate from any direct effect on MNEs with their own Chinese operations. The JV and WFOE exposures

[21] Because the included US firms have no Chinese affiliates, the numerator of each industry exposure—the domestic sales of Chinese JV (or WFOE) affiliates in that industry—is common to all US firms in the estimation sample. In a robustness check that includes all US firms, we subtract each MNE's own JV and WFOE affiliates' domestic sales from the numerator.

Table 2: JV and Negative Outcomes for US Firms (OLS)

Dep. var.	ΔSale		ΔEmp.		ΔCapital		ΔExport		ΔR&D		ΔPatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
ΔJV_j	−14.27***	−16.10***	−15.51***	−16.18***	−11.76***	−13.44***	−13.38***	−18.73***	−15.50***	−19.98***	−4.31**	−5.17**
	(2.62)	(2.39)	(3.33)	(2.94)	(3.24)	(3.36)	(4.69)	(4.37)	(2.82)	(3.28)	(1.85)	(2.13)
$\Delta WFOE_j$	9.07	3.51	17.83**	6.14	7.30	−1.14	21.08	11.06	13.73	−2.80	13.15***	8.25**
	(6.04)	(4.65)	(8.19)	(4.78)	(8.94)	(6.11)	(12.70)	(7.70)	(9.02)	(7.67)	(4.91)	(4.00)
$NTRgap_j$	−2.06**	−2.29***	−2.12**	−2.49***	−2.15***	−2.40***	−2.78*	−2.93**	−2.58***	−2.82***	−0.03	−0.22
	(0.79)	(0.71)	(0.91)	(0.78)	(0.80)	(0.69)	(1.46)	(1.37)	(0.82)	(0.76)	(0.21)	(0.17)
Controls		✓		✓		✓		✓		✓		✓
Mean dep. var.	7.84	7.84	−11.27	−11.27	9.75	9.75	27.89	27.89	−1.30	−1.30	74.45	74.45
# clusters	105	105	105	105	105	105	99	99	77	77	99	99
N	949	949	949	949	949	949	767	767	462	462	769	769

Notes: Standard errors clustered at the SIC 3-digit level are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports OLS estimates of equation (3.3) for US firms. ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). 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 over 1999–2012. The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. The even columns include the same set of additional controls in Table 1. All regressions are weighted by initial sales.

are defined at the 4-digit SIC level as in equations (3.4) and (3.5): the domestic sales growth of Chinese JV and WFOE affiliates in each industry. Standard errors are clustered at the 3-digit SIC level.

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 JV exposure of industry j is associated with a 0.14 percentage point lower sales growth rate over the same period for a US firm in that industry. The result remains stable in column 2, which adds the same controls used in the Chinese spillover regression along with pretrend variables. If pretrends were driving these negative correlations, we would expect meaningful changes in the estimates, which we do not find. We directly explore pretrends below.

JV exposure was also negatively correlated with employment, capital, and export growth, and innovation measures including R&D growth and cumulative patent counts. These innovation results are consistent with Autor et al. (2020), who found a negative impact of the China trade shock on US firms' innovation outcomes. One possible interpretation is that JV from the US to China may have contributed to the decline in US manufacturing, a finding our quantitative analysis later reproduces.

In addition, JV exposure is negatively correlated not only with US firm outcomes but also

with the outcomes of firms in other high- or low-income countries, further supporting the idea that JVs into China intensified global competition through direct and indirect positive spillovers to Chinese firms (Appendix Table B6).[22] In particular, the negative correlation for firms in low-income countries further suggests that our results are unlikely to be driven by sectoral technological trends among advanced economies.

Pretrends Cannot Explain Facts 2 and 3. We next show that pretrends cannot explain the positive spillovers to Chinese firms or the negative outcomes for US firms. On the China side, our data start in 1998, so we use 1998 as the base year for constructing the JV and WFOE exposures; we therefore test for pretrends using sectoral gross-output and value-added growth from China's National Bureau of Statistics over 1995–1997, regressing these on the JV and WFOE exposures. On the US side, we regress firm-level outcome growth over 1993–1998 on the same two exposure variables. Table 3 reports the results. China's sectoral growth (1995–1997) in Panel A and US firm-level growth (1993–1998) in Panel B are uncorrelated with JV exposure, with magnitudes that are small both statistically and economically. JV exposure remains insignificant after controlling for WFOE exposure and the NTR gap. These findings indicate that Facts 2 and 3 are not driven by sectoral pretrends on either side.

IV Strategy and Robustness Checks for Facts 2 and 3. The OLS estimates for spillovers and negative outcomes for US firms may suffer from endogeneity. To alleviate this concern, we consider two IV strategies. First, we use industry-level changes in FDI by Korean and Japanese MNEs into India as an IV. This exploits push factors driving these countries' FDI into China, which are arguably exogenous to factors specific to the US-China pair. Second, we use changes in industry-level indicators for the FDI regulations based on the Catalogue for the Guidance of Foreign Investment Industries over 1998–2007, an IV first proposed by Lu et al. (2017).[23] Appendix B.2 discusses these two strategies and their identifying assumptions in detail. The IV estimates are larger in magnitude than the OLS estimates. They could be

[22] High-income countries include Australia, New Zealand, Singapore, South Korea, Japan, and the Western European countries.

[23] Since 1995, the Catalogue has provided guidelines for FDI, which were gradually relaxed in 1997, 2002, 2004, and 2007. For example, in 2017, in the automobile industry, Chinese partners' ownership share could not fall below 50%. Airplane manufacturing was restricted to JVs, while rare earth exploration, mining, and processing remained completely closed to FDI. The policy change data come from Brandt et al. (2017).

Table 3: Pretrends Cannot Explain Positive Spillovers to Chinese Firms and Negative Outcomes for US Firms (OLS)

Panel A. China Pretrends (Sector-Level)

Dep. var.	ΔGross output (1995–1997)		ΔValue-added (1995–1997)	
	(1)	(2)	(3)	(4)
ΔJV_j	−0.00	−0.01	−0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta WFOE_j$		−0.01		−0.06
		(0.06)		(0.06)
$NTRgap_j$		−0.00		−0.00
		(0.00)		(0.00)
Mean dep. var.	0.20	0.20	0.26	0.26
# Clusters	157	157	157	157
N	379	379	379	379

Panel B. US Pretrends (Firm-Level)

Dep. var.	ΔSale (1993–1998)		ΔEmp (1993–1998)		ΔCapital (1993–1998)	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔJV_j	−0.29	−1.36	−0.22	−1.61	0.85	0.07
	(1.23)	(1.92)	(1.15)	(1.61)	(0.96)	(1.26)
$\Delta WFOE_j$		−4.16		−4.71		−5.14
		(8.69)		(6.51)		(11.13)
$NTRgap_j$		−0.26		−0.34		−0.17
		(0.34)		(0.29)		(0.19)
Mean dep. var.	17.11	17.11	5.83	5.83	19.03	19.03
# clusters	97	97	97	97	97	97
N	594	594	594	594	594	594

Notes: Standard errors clustered at the CIC and SIC 3-digit level are reported in parentheses in Panels A and B, respectively. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports OLS estimates of equation (3.3) for US firms. ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). In columns 1–2, 3–4, and 5–6 of Panel B, the dependent variables are DHS growth of US firms' sales, employment, capital, exports, R&D, and cumulative patents between 1993–1998. The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. All regressions are weighted by initial gross output in Panel A and sales in Panel B.

biased if the instruments are correlated with unobserved technological changes. To assess the extent of this potential omitted variable bias, we follow Borusyak et al. (2022) and include observables related to such changes as additional controls. The IV estimates remain stable.

We also conducted additional robustness checks for Facts 2 and 3 (see Appendix Table B7). 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.

To summarize, these findings reinforce the inference that joint venture investment in China benefited Chinese firms, even those not involved in joint ventures, but negatively affected US firms over time, as the growth of Chinese firms intensified competition in the global market.

4. Theoretical Framework

In this section, we develop a two-country growth model with oligopolistic competition, innovation, and joint ventures, to study the role of joint ventures in the growth of Chinese and US firms and the welfare and policy implications. In our model, JVs are the only form of FDI, and we do not separately model acquisitions of existing firms or the creation of WFOEs.

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. The tradable sector comprises a unit-mass continuum of products (or industries) $j \in [0, 1]$; each firm produces a unique variety within a product. Varieties are tradable across countries subject to iceberg trade costs $\tau^x \geq 1$ (a firm ships τ^x units to deliver one unit abroad) and import tariffs $t_{Ct} \geq 0$. The non-tradable sector consists of a representative firm in each country. Each country has a representative household, immobile across countries, who owns all domestic firms and supplies labor inelastically. There is no trade in assets, ruling out international borrowing and lending.

For each product j in the tradable sector, there are three types of firms: leaders (Home and Foreign), fringe firms (Home and Foreign), and JVs (Foreign). JVs can be established through mutual agreements between the leaders from the two 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 firm composition in Home remains fixed. The sets of firms for product j at time t are $\mathcal{I}_H = \{h, \tilde{h}\}$ for Home and $\mathcal{I}_{Fjt} = \{f, \tilde{f}, v\}$ for Foreign, where h and f are leaders, $\tilde{h}$ and $\tilde{f}$ are fringe firms, and v is a JV. Only JVs have

entry and exit margins.

4.2 Household

A representative household in Home maximizes utility subject to a budget constraint,

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

where C_{Hs} is final consumption good (price index P_{Ht}), $\rho > 0$ is discount rate, r_{Ht} is interest rate, L_H is labor endowment, and w_{Ht} is wage. We take the Home wage as the numeraire. 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}. The asset is claims to firms' profits. Its Euler equation, which pins down the interest rate in a no-trade equilibrium, is: $\frac{\dot{C}_{Ht}}{C_{Ht}} = r_{Ht} - \left(\rho - \frac{\dot{P}_{Ht}}{P_{Ht}}\right)$.

A household has Cobb-Douglas preference over the tradable and non-tradable sector output (C^T_{Ht} and C^N_{Ht}):

$$C_{Ht} = (C^T_{Ht})^\beta (C^N_{Ht})^{1-\beta}, \qquad P_{Ht} = \left(\frac{P^T_{Ht}}{\beta}\right)^\beta \left(\frac{P^N_{Ht}}{1-\beta}\right)^{1-\beta}, \quad (4.2)$$

where β denotes the expenditure share of the tradable sector, and P^T_{Ht} and P^N_{Ht} denote the price indices of tradable and non-tradable sector output, respectively.

4.3 Sectors

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

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

where y_{ijt} and y^*_{ijt} are the quantities of varieties produced by domestic and foreign firms indexed by i within 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 ($\psi = \psi_h = \psi_f = \psi_v$), while fringe firms have a different common value ($\tilde{\psi} = \psi_{\tilde{h}} =$

$\psi_{\tilde{f}}$), which are normalized such that $\psi + \tilde{\psi} = 1$. Varieties are imperfectly substitutable within products, with the elasticity of substitution $\sigma \in (1, \infty)$. Because we do not want the introduction of a new variety by forming a JV to mechanically increase utility, we neutralize the love of variety by normalizing the product-level aggregator with the sum of all firms' demand shifters $\sum_{i \in \mathcal{I}_{jt}} \psi_i$, where $\mathcal{I}_{jt} = |\mathcal{I}_H \bigcup \mathcal{I}_{Fjt}|$ (Benassy, 1996). 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: $Y_{Ht}^N = Z_{Ht}^N L_{Ht}^N$, where Z_{Ht}^N is exogenous productivity, which grows at rate g^N. With perfect competition, $P_{Ht}^N = \frac{w_{Ht}}{Z_{Ht}^N}$.

4.4 Firms

Production and Market Structure. A firm indexed by i produces a variety within product j using a production function that 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 market clearing condition: $\mathcal{Y}_{ijt} = y_{ijt} + \tau^x y_{ijt}^*$.

Within each product, the two leaders (Home and Foreign) and the JV (if established) 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

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

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

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

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

Unlike the other types of firms, we assume that 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 $p_{\tilde{h}jt}^* = \frac{\sigma}{\sigma-1}\frac{\tau^x(1+t_{Ft})w_{Ht}}{z_{\tilde{h}jt}}$ and their operating profits are $\pi_{\tilde{h}jt} = \frac{1}{\sigma}s_{\tilde{h}jt}P_{Ht}^T C_{Ht}^T$ and $\pi_{\tilde{h}jt}^* = \frac{1}{\sigma}s_{\tilde{h}jt}^* P_{Ft}^T C_{Ft}^T$. Fringe firms can be interpreted as a continuum of atomistic, homogeneous firms whose total mass is 1.

Innovation. Leaders (both Home and Foreign) can improve productivity through successive innovations. They choose the Poisson arrival rate of innovation, x_{ijt}, subject to the following convex cost function:

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

where h_{ijt}^r is R&D workers employed by firm i, and α_{cr} and γ are parameters that govern the scale and curvature of innovation costs in country 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 (Grossman and Helpman, 1991; Aghion et al., 2001).

Fringe firms do not innovate. Their productivity improves only via technology diffusion from domestic leaders within products.

Joint Venture. A Home leader may collaborate with the Foreign leader in the same product category 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 back to Home. Home leaders' incentives to form a JV increase with Foreign market size, wage differentials, and trade costs, capturing the proximity-concentration trade-off (Helpman et al., 2004).[24]

[24]Because JVs can export back to Home, our model also captures the idea that Home leaders may use JVs as export platforms to serve their own markets by leveraging lower labor costs abroad (Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017).

The JV firm has productivity $z_{vjt} = \frac{z_{hjt}}{\tau^z}$, where $\tau^z > 1$ captures the productivity loss from multinational production. This loss reflects barriers to operating in a foreign regulatory environment as well as additional management and communication costs (Holmes et al., 2015; Arkolakis et al., 2018). The JV does not innovate. Its productivity rises passively with the Home leader's z_{hjt}, consistent with Bilir and Morales (2020), who document productivity spillovers from MNE-headquarters R&D to foreign affiliates. This sharing of headquarters' productivity with JVs reflects the nonrivalry of ideas.[25]

We assume that JVs maximize their own profits rather than jointly maximizing total profits with their parent firms.[26] The Home leader receives a κ fraction of the JV's total profits Π_{vjt}, while the Foreign leader retains the remaining $1-\kappa$ fraction. This fraction κ is fixed across JVs and taken as given by firms. While richer contractual arrangements may affect welfare and joint venture formation, we adopt this constant-split rule for two reasons. First, it is consistent with the Chinese JV Law, which required MNEs and Chinese partners to share JV profits in proportion to their equity stakes.[27] Second, a constant split allows us to focus on the negative competition effects on US fringe firms.

A Home leader chooses the Poisson arrival rate of an opportunity to form a JV, d_{hjt} by hiring h^d_{hjt} workers:

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

where α_{Hd} governs the scale of the cost. We impose the same curvature parameter as in innovation due to the lack of information on the costs of setting up JVs.[28] h^d_{hjt} represents expenses for training local managers or legal processing costs associated with setting up a new firm.

[25]This nonrivalry is also consistent with Burstein and Monge-Naranjo (2009) and Holmes et al. (2015) who model firm-embedded productivity (e.g., blueprints, managerial practices, and intangible capital) as shareable across countries. Alviarez et al. (2023) find that such shareable firm-specific productivity explains one-third of the cross-country variance in output per worker.

[26]This can be micro-founded through an agency problem, where the JV manager maximizes only the JV's profit, not the joint profit with its parents. Thomas (2011) also provide empirical evidence that each division within multinational manufacturers maximizes its own profits, rather than coordinating to maximize total MNE profits, in the laundry detergent industry.

[27]Article 4 of the JV Law requires that "the parties to the venture shall share the profits, risks and losses in proportion to their respective contributions to the registered capital." We treat κ as the cross-JV average equity share; in practice, regulatory caps (often 50 percent for the foreign party) made shares cluster in a narrow range.

[28]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.

With successful rate of d_{hjt}, Home and Foreign leaders engage in a Nash bargaining, which determines the one-time fee C_{jt} that the Home leader pays (or receives, if negative), 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 power.[29] Once established, a JV operates until it exits exogenously at rate χ.

Technology Diffusion. There are three types of technology diffusion. First is direct diffusion through JVs, between the two partners of each JV. While operating, the lagging partner (Home or Foreign leader) directly learns from its more advanced partner, catching up to that partner's productivity with Poisson intensity ϕ, capturing Fact 1.[30] We assume that technology transfer occurs not only for existing technologies at the time of the contract but also for subsequent innovation. This creates technology leakage effects that reduce the innovation rate after JV formation, consistent with evidence that US firms' innovation declines with JV exposure (Fact 3).

The second is within-country diffusion. Fringe firms catch up with the domestic leader's productivity level with Poisson intensity δ^D.[31] We assume δ^D is the same in both Home and Foreign. JVs also indirectly benefit Foreign fringe firms through this within-country diffusion (Fact 2).

The third is between-country diffusion. With Poisson intensity of δ^F, the lagging leader within product j catches up to the productivity of the advanced leader. δ^F captures knowledge diffusion between countries through channels other than JVs.[32]

[29]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 the 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.

[30]Such "immediate" catch-up implies that firms gains more from diffusion, when they are lagged behind, which captures the advantage of backwardness (Gerschenkron, 1962). Previous papers have also imposed a similar process (Aghion et al., 2001; Akcigit et al., 2024; Sui, 2025; Choi and Shim, 2024).

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

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

4.5 Equilibrium

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

State Variable. The technology gap between the Home and Foreign leaders in product j can be expressed as

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

$m^F_{jt} \in \{-\bar{m}, \ldots, 0, \ldots, \bar{m}\}$ is the size of the technology gap. $m^F_{jt} > 0$ implies that the Home leader has higher productivity than the 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, the within-country technology gaps between leaders and fringe firms for 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 the JV status and other aggregate variables, $\mathbf{m}_{jt}$ determines profits of each firm within product j.[33] Because products are symmetric, we drop all subscripts of $\mathbf{m}_{jt}$ and sector-specific subscripts in firm-level variables for notational convenience.

Value Function. Let $V_{ht}(\mathbf{m}; \mathcal{J})$ denote the value function of the Home leader h in a product given a state variable $\mathbf{m}$, with $\mathcal{J} \in \{0, 1\}$ denoting the JV status. Here we present only value functions of Home leaders when they are m^F steps ahead of their respective Foreign leader (i.e., $m^F > 0$). The value functions for other cases are provided in Appendix C.

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

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

[33] Because we assume that the productivity of the JV is tied to the Home leader's productivity, we do not have to separately keep track of the JV productivity.

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

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

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

The value function when $m^F > 0$ and a JV is already established 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 flow profits include those generated by the JV ($\kappa\Pi_{vjt}$). Because the JV is already established, leaders no longer engage in new JV formation ($d_{ht} = 0$). The first term of the third line accounts for direct diffusion that the Foreign leader may catch up with the Home leader's productivity level thanks to the JV. The second term of the same line represents the change in value due to the exogenous exit of the JV.

Optimal Investment in Innovation and Joint Ventures. The innovation and JV rates are functions of technology gaps $\mathbf{m}$. The optimal innovation rate can be expressed as

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

Similarly, the optimal joint venture rate can be written as follows:

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

Bargaining and Joint Venture Fees. With a successful JV formation rate d_{hjt}, the Home leader within a product pays (or receives) a fee to (or from) the Foreign leader, determined through Nash bargaining:

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

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

When Foreign leaders lag further behind (i.e., $m^F > 0$), Home leaders are more likely to receive JV 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 lower profits in the future due to productivity improvements among Foreign firms due to both direct and indirect technology diffusion through JVs. They internalize these dynamic profit losses and are compensated through bargaining fees by Foreign leaders. However, they do not care about the profit losses incurred by Home fringe firms due to the JV formation. This creates a reason why there may be over-investment in JVs relative to what is optimum for the US as a whole. Similarly, Foreign leaders do not internalize the benefit of technology diffusion to Foreign fringe firms, which may imply under-investment in JVs from the Chinese perspective.

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

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

The optimal JV rate increases with the total surplus $(\Delta^{\text{JV}} V_{Ht} + \Delta^{\text{JV}} V_{Ft})$, 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 value of all Home firms. For each tradable product indexed by j, the goods market clears:

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

where we used the fact that the expenditure shares of all products are equal, given the unitary elasticity assumption across measure one of products indexed by j. The goods markets in tradable and non-tradable sectors clear: $Y^T_{Ht} = C^T_{Ht}$ and $Y^N_{Ht} = C^N_{Ht}$. Labor markets clear:

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

where the right-hand side is the sum of labor demand by Home firms for production, innovation, and joint venture investment, as well as by the representative non-tradable firm. Similar market clearing conditions hold in Foreign, which are omitted here to save space.

The balance of payment equation is as below:

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

where the left-hand side is the sum of imports from Foreign and JV fee payments to Foreign, and the right-hand side is the sum of exports and the share of JV profits distributed to Home.

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

Definition 1. *A Markov perfect equilibrium consists of sequences of prices* $\{r_{ct}, w_{ct}, p_{ijt}, p^*_{ijt}, P^T_{jt}, P^N_{jt}, P_{jt}\}$ *and allocations* $\{l_{ijt}, x_{ijt}, d_{ijt}, y_{ijt}, y^*_{ijt}, L^N_{ct}, C^N_{ct}, C^T_{ct}, C_{ct}\}$ *such that (i) the representative household maximizes utility; (ii) firms maximize the present discounted value of profits; (iii) goods, labor, and asset markets clear in every country c and period t; and (iv)* $\mu_t(\mathbf{m};\mathcal{J})$ *evolves according to firms' optimal innovation* (x_{ijt}) *and joint venture* (d_{ijt}) *investments.*

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.*

The two countries share a common growth rate on the balanced growth path. Given initial conditions, however, growth rates differ along the transition, and JVs accelerate China's convergence to the balanced growth path.

Welfare. To evaluate welfare effects of policies on JVs, we define a consumption-equivalent welfare measure ω as the percentage increase in lifetime consumption that makes the representative household in the baseline economy indifferent between the baseline and the counterfactual:

$$\int_t^\infty \exp\big(-\rho(s-t)\big)\ln\big((1+\omega)C^b_{Hs}\big)\,\mathrm{d}s = U^c_{Ht}, \tag{4.11}$$

where C^b_{Ht} is the consumption path in the baseline economy and U^c_{Ht} is the present-discounted utility under the counterfactual.

4.6 Taking Stock

Market Failure. One novel feature of our model is the negative impact of Home leaders' JVs and technology transfer on Home fringe firms, which the leaders do not care about. Direct and indirect technology diffusions through JVs to Foreign firms enhance their global competitiveness, reducing Home firms' profits. Home leaders internalize their own future profit losses due to rising competition, when making JV decisions. Technology diffusion intensities (ϕ, δ^D), and leaders' demand shifters, ψ, govern the magnitude of Home leaders' over-investment in JVs relative to what is optimal for the Home country as a whole.

Higher diffusion rates intensify future competitive pressures on Home fringe firms. Higher demand shifters mean leaders hold larger market shares, in which case they align their JV decisions more closely with total industry profits and what is socially optimum. It is important that Home fringes do produce in equilibrium for Home leaders' JV decisions to deviate meaningfully from the social optimum for the Home country.

Beyond this, our model features other common market failures of step-by-step innovation frameworks. Technology diffusion is a classic positive externality, implying that there may be too little innovation. At the same time, given the business stealing effects, there may be over-investment in innovation. Oligopolistic market structure causes firms to produce below socially optimal levels.

The Two-Country Assumption. Our model builds on a two-country framework to operationalize strategic interactions between firms while maintaining computational feasibility. Under this assumption, 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 if US JVs are restricted. Furthermore, strategic interactions could emerge between the US and Japan. Competing foreign firms may race to transfer technology 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 form JVs in China, as the strategic pressure to transfer technology weakens. Therefore, the two-country assumption may not necessarily exaggerate the role of US JVs in Chinese growth. We leave a three-country extension to future research.

5. Taking the Model to the Data

Each product in the tradable sector maps to a 4-digit SIC manufacturing industry. We solve the model's transition dynamics from 1997 until convergence to a balanced growth path; no JVs exist in 1997. Calibrating along the transition matters because China experienced rapid growth over our sample period. Initial technology gaps between US and Chinese leaders are drawn from a normal distribution $N(\mathcal{D}, \mathcal{V})$, with mean $\mathcal{D}$ and variance $\mathcal{V}$. A positive $\mathcal{D}$

Table 4: Calibration Summary

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^N	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. across varieties	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. tech. diffusion across 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 tech. 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. tech. diffusion within country	Sectoral regression results in China, Table 1

means that, on average, US leaders start with higher productivity than Chinese leaders.

We calibrate 24 parameters in three steps: 10 are taken directly from the data, 4 are externally calibrated from the literature, and 10 are jointly estimated by simulated method of moments (SMM). For each guess of the 10 jointly estimated parameters, we solve the model's transition, compute the implied moments, and measure their distance from the data; we select the parameters that minimize this distance.

We take the 10 parameters $\{L_H, L_F, \beta, \chi, \kappa, \xi, g^N, \mathcal{V}, t_t^H, t_t^F\}$ directly from the data. Home labor is normalized to $L_H = 1$, and Foreign labor is set to $L_F = 2.83$ based on the human-capital-adjusted population of China relative to the US (Lee and Lee, 2016). The consumption share of tradables β is set to 0.4 from the 1997 US Benchmark Input-Output table. The exit rate of JVs χ is set to 0.08 from the average exit rate of Chinese firms in Chen et al. (2023). The tariffs t_t^H and t_t^F are computed as import-weighted annual averages across manufacturing sectors.

The US JV profit share κ is set to 0.54, the average equity share of MNEs in JV firms in Orbis, consistent with the JV Law's mandate of equity-proportional profit sharing. Lacking

direct data on licensing fees between US and Chinese firms, we set the US leaders' bargaining power ξ to the same value, 0.54.[34] The non-tradable growth rate g^N is set to match the average growth rate of US real GDP per capita over 2011–2019. The variance $\mathcal{V}$ is set to 0.7, the variance of US-China labor productivity ratios across manufacturing industries in 1999.

The 4 parameters $\{\rho, \sigma, \gamma, \tau^x\}$ are externally calibrated from the literature. We set the discount rate $\rho = 0.03$. We set $\gamma = 2$, 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 $\mathbf{\Theta} = \{\alpha_{Hr}, \alpha_{Fr}, \alpha_{Hd}, \lambda, \mathcal{D}, \phi, \tau^z, \psi, \delta^F, \delta^D\}$ are jointly estimated by minimizing the distance between model moments $M_m(\mathbf{\Theta})$ and their data counterparts M_m^D:

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

We discuss the identification of each parameter below.

The US R&D cost scale parameter α_{Hr} is calibrated to match the average R&D-to-sales ratio among manufacturing firms in Compustat. China's α_{Fr} is calibrated so that both countries reach the same average productivity level on the balanced growth path.[35] The JV cost scale parameter α_{Hd} is estimated to match the sales share of JVs in China; this moment is informative because higher JV costs reduce JV investment and therefore JV sales shares. The step-size parameter λ governs the long-run growth rate, so we calibrate it to match the US average GDP growth rate over 2011–2019.

The initial gap $\mathcal{D}$ is calibrated to match the 1999 ratio of value-added per employee between China and the US. The between-country diffusion parameter δ^F is calibrated to match the 2020 ratio of value-added per employee between the two countries, which we take as the long-run target. A higher δ^F implies faster Chinese convergence. The leaders' demand

[34] To pin down ξ, we would need direct data on royalty payments between US and Chinese firms. Our value of 0.54 falls within the range of comparable models with bargaining between innovators and adopters: 0.25 in Santacreu (2025), chosen as a common heuristic in licensing negotiations, and 0.85 in Choi and Shim (2024), who calibrate the bargaining parameter to match Korean firms' payments for technology transfers. We later show that with this value, the model reproduces the licensing payments from foreign affiliates to US MNE parents reported in BEA data on US multinationals, as a non-targeted moment.

[35] This calibration yields $\alpha_{Fr} > \alpha_{Hr}$ because China has a larger labor endowment: at $\alpha_{Hr} = \alpha_{Fr}$, average Chinese productivity on the balanced growth path would exceed US productivity. The calibrated α_{Fr} captures Chinese firms' R&D costs net of any time-invariant R&D subsidies (if any); we do not separately identify the subsidy component or model its fiscal cost.

shifter ψ is calibrated to match the share of US Compustat manufacturing-firm sales in total US gross manufacturing output (Brault and Khan, 2024). We thereby treat publicly listed manufacturers in Compustat as the empirical counterpart of the model's leader firms—the firms with the scale and resources to form joint ventures abroad. This is also consistent with our Orbis data, where publicly listed US firms account for the bulk of US outbound FDI to China (72% of JV-affiliate sales and 82% of WFOE-affiliate sales by US firms in 1999).

We pin down the direct diffusion parameter ϕ, the within-country diffusion parameter δ^D, and the JV iceberg technology cost τ^z using Facts 1, 2, and 3, respectively. Appendix D.1 describes the procedure in detail. We calibrate ϕ by running the diff-in-diff regression analogous to equation (3.1) on model-generated data, matching the average of the post-event coefficients.[36] The within-country diffusion parameter δ^D relates directly to Fact 2. The JV iceberg cost τ^z captures the JV's productivity loss, so a higher value implies a weaker competition effect on US fringe firms, linking it to Fact 3. To calibrate these two parameters, we run regressions analogous to equation (3.3) on fringe firms in the US and China, fitting the OLS estimates in column 1 of Tables 1 and 2.[37]

Table 4 summarizes the estimation results. The model moments closely match their data counterparts (Panel A of Table 5). We obtain $\mathcal{D} = 20.0$, implying that the productivity of US 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 between leaders from 2.4% to 15.4%. $\tau^z = 1.84$ suggests that JV productivity is 46% lower than that of their US leaders'.

The model also matches three non-targeted moments (Panel B of Table 5). First, it predicts a positive relationship between the initial US-China productivity gap and sectoral JV exposure: larger gaps make JVs more attractive because they generate higher JV profits and larger gains from diffusion, a pattern we also see in the data. Second, it reproduces the observed negative effect of JV exposure on US firms' R&D (col. 11, Table 2)—a higher probability of technology diffusion and partial capture of JV profit reduce the return to successful innovation. Finally, in the calibrated model, the average ratio of JV fee flow to JV sales flow is 1.36%, which falls

[36] Specifically, we run $y_{imt} = \beta(\mathbb{1}[\text{Post}_{mt}] \times \mathbb{1}[\text{JV Partner}_i]) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}$, where the estimated β averages the post-event coefficients in equation (3.1), equal to 0.2 in our data.

[37] The restriction to fringe firms is consistent with the JV exposure measure, which excludes own JV affiliates.

Table 5: 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	−0.143
CN indirect effects of JV on sales (col 1, Panel A, Table 1)	0.083	0.077
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
JV fee / JV sales ratio (%) (Branstetter et al., 2006)	1.36	1.50

Notes. This table reports targeted and non-targeted moments in the model and the data.

within the range reported by Branstetter et al. (2006) from US BEA microdata.[38]

6. Quantitative Exercises

6.1 Did US Multinationals Transfer Too Much Technology to China?

Using the calibrated model, we first examine whether the US transferred too much technology to China through JVs. We consider a counterfactual scenario in which the US government bans new JV investments from 1999 onward, and compare its welfare to the baseline with JVs. Existing JVs remain in place until they exit exogenously. We treat this policy change as an unanticipated shock to all agents in 1999.

[38]The BEA's US Direct Investment Abroad surveys require US multinationals to report the affiliate-level value of royalties paid by foreign affiliates to parent firms for the sale or use of intangible property (e.g., technology licensing fees and use of trademarks). Branstetter et al. (2006) report that annual royalties as a share of affiliate sales average around 1–1.5%. Because the JV fee is a one-time payment, we convert it to an instantaneous-flow equivalent $\tilde{C}_i$ from $C_{it} = \int_t^\infty e^{-\rho(s-t)}\tilde{C}_i ds$. The corresponding ratios of fees to US and Chinese leaders' sales are 2.78% and 3.67%. The ratio is lower for the JV because the JV has the largest sales: it operates with the US leader's productivity, lower Chinese wages, and no iceberg trade costs on Chinese sales.

Table 6: Baseline vs. Counterfactual Scenarios: Welfare Effects (%)

JV restriction	in 1999	in 1999 coordinated JV	in 1999 technology gap ≥ 6	in 2025
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: (1) restricting new JVs from 1999 onward; (2) restricting new JVs from 1999 onward with coordinated JV decisions in both the baseline and counterfactual; (3) restricting new JVs from 1999 onward only for technology gaps $m^F \geq 6$; and (4) restricting new JVs from 2025 onward. In each counterfactual, welfare is computed relative to the baseline with no restriction, with positive values indicating that the restriction raises welfare. For columns 1–3, welfare is measured from 1999 onward; for column 4, from 2025 onward.

Table 6 reports the consumption-equivalent welfare effects. The JV restriction in 1999 raises US welfare by 1.20% but reduces China's welfare by 10.25%.[39] In the counterfactual, the US-China technology gap widens and China's convergence slows (Panels A and B of Figure 2). Without JV-driven technology diffusion, Chinese leaders' productivity grows more slowly, while US leaders' productivity rises slightly due to higher innovation rates (Panel C, counterfactual minus baseline).[40] We explain below why US leaders innovate more when JVs are banned. Without JVs, Chinese firms substitute innovation for the missing technology diffusion, raising R&D, but the increase does not fully compensate for the lost diffusion.

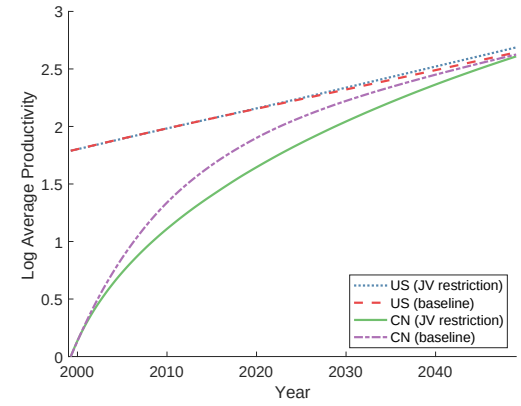
Although the net welfare change is positive for the US and negative for China, Panel D of Figure 2 reveals richer consumption dynamics. The lines plot counterfactual consumption divided by baseline consumption for each country. US consumption falls immediately after the JV restriction as US leaders lose JV fees and profits. Over time, however, higher US productivity and innovation boost US firms' global competitiveness, and US consumption under the restriction surpasses the baseline after about 20 years. China's consumption initially declines as productivity growth slows, but gradually recovers after roughly 20 years as the technology gap narrows and diffusion matters less once both countries approach their respective balanced growth paths.

Three forces shape US innovation rates under the JV ban. The option-value and market-

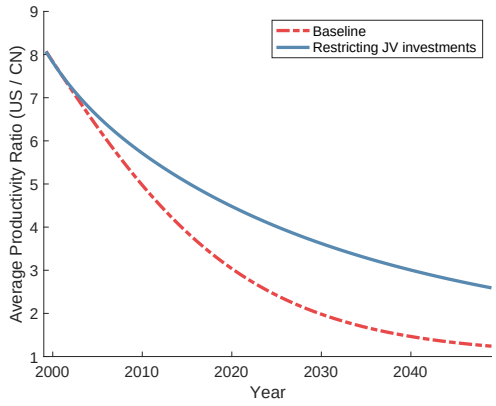
[39] Defining global welfare as a weighted average $W = \Lambda U^{US} + (1-\Lambda)U^{CN}$, the restriction lowers global welfare whenever $\Lambda < 0.89$.

[40] Chinese productivity grows at 8.6% per year on average in our baseline over 1999–2025, close to the 8% rate Brandt et al. (2012) estimate from firm-level TFP for 1998–2007.

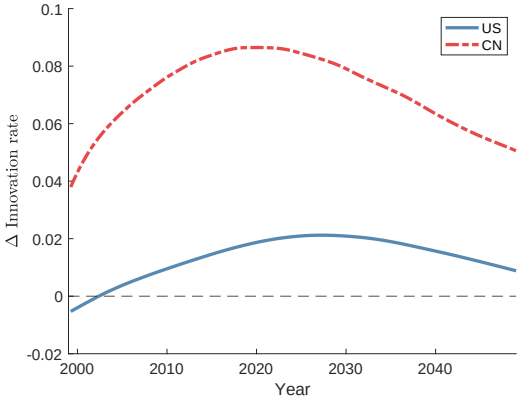
Figure 2: Effects of Banning Joint Venture Investments in 1999: Dynamics of Productivity, Innovation, and Consumption



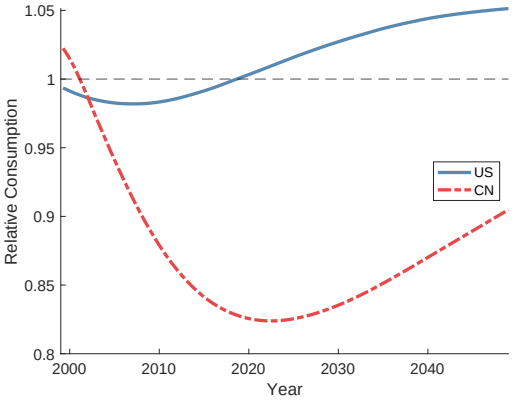
A. Log leader productivity



B. Productivity ratio (US/China)



C. Innovation rate (counterfactual − baseline)



D. Consumption (counterfactual / baseline)

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

size effects push innovation higher when JVs are available; the leakage effect works in the opposite direction. The *option-value effect* is the incentive to innovate before forming a JV: by raising productivity, US leaders increase the total JV surplus and capture part of it through Nash bargaining. The *market-size effect* is the standard market-access channel: JVs enlarge effective market size and raise marginal returns to R&D. The ban removes both, depressing innovation, which explains why the average innovation rate drops immediately after the 1999 ban (Panel A of Figure 3).

The *leakage effect* works the other way: JVs accelerate technology spillovers to Chinese rivals, eroding future profits and dampening returns to innovation (Helpman, 1993).[41] Any extra innovation surplus that benefits the Chinese partner cannot be recouped once the JV fee is paid. At the product level, the leakage effect dominates the market-size effect: products with JVs exhibit lower innovation intensities than those without, conditional on technology gaps (Panel B of Figure 3).[42] In our calibration, as JVs are established in more products, the overall mix shifts toward products with lower innovation rates.[43] Over the medium term, this composition shift—driven by the dominance of the leakage effect—outweighs the option-value and market-size effects, raising average innovation rates under the JV ban.[44]

Next, we decompose the welfare effect of restricting JVs by income source (Table 7). Real income is the sum of discounted leader profits (own profits + JV profits + JV fees), fringe profits, and labor income (real wage), each normalized by the country's baseline real income. For the US, leader profits fall in the counterfactual because JV profits and JV fees from Chinese partners are lost. Fringe profits rise both because JV competition is removed and because reduced technology diffusion weakens competition from Chinese firms. The real wage rises for two reasons: higher domestic labor demand, and lower prices driven by higher US innovation. The price channel is partly muted under the baseline because JV decisions are driven not only by lower production costs but also by JV fees, so the price decline from JVs need not fully offset the reduction in domestic labor demand.

The large general-equilibrium amplification on the US side—operating through labor

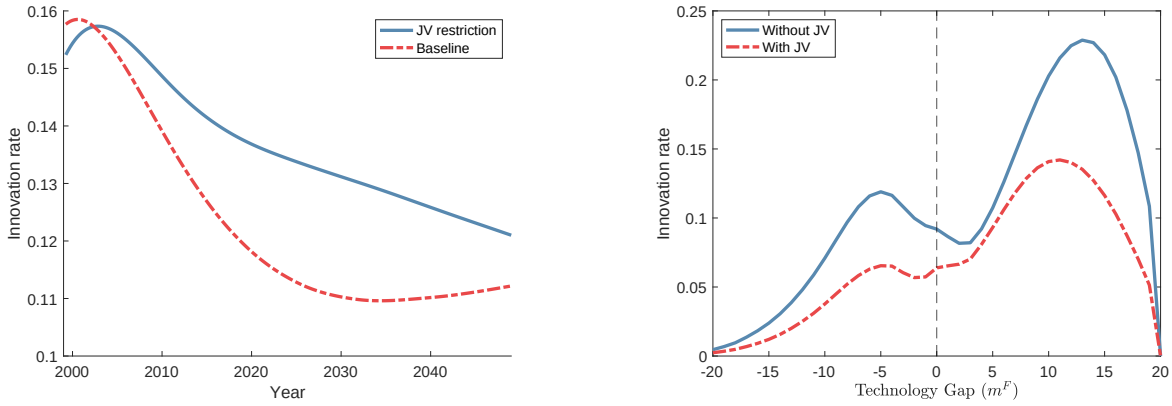
[41] In the context of intellectual property rights, Helpman (1993) shows that imitation (or diffusion) reduces the expected return to R&D investment because innovators anticipate that competitors will erode their market position by imitating their innovation.

[42] The two peaks in Panel B arise from escape-competition effects (Akcigit et al., 2023). The peak at $m^F \approx -5$ reflects a "defensive" motive: US and Chinese leaders are neck-and-neck in the US market (after accounting for wage differentials and trade costs), so even a small productivity gain sharply raises domestic profits and prompts US leaders to innovate more to defend their domestic market share. The peak at $m^F \approx 13$ reflects an "expansionary" motive: US leaders are neck-and-neck in the Chinese market, so they raise R&D to expand abroad. The asymmetry between the peaks (−5 vs. 13) reflects China's lower wages. One difference from Akcigit et al. (2023) is that JV-driven diffusion tends to close the productivity gap toward zero, where innovation rates fall below the two peaks.

[43] In Appendix Figure D1, we consider two alternative parameterizations. Setting $\kappa = 1$ assigns the entire JV profit to US leaders, amplifying the market-size effect; the gap in innovation rates between the baseline and counterfactual then narrows. Shutting down direct diffusion by setting $\phi = 0$ eliminates the leakage effect; the sign of the innovation-rate difference then flips, with baseline innovation rates exceeding counterfactual rates.

[44] This result is consistent with the observation by Andy Grove, a former CEO of Intel: "Our pursuit of our individual businesses . . . often involves transferring manufacturing and a great deal of engineering out of the country . . . We don't just lose jobs—we lose our hold on new technologies and ultimately damage our capacity to innovate" (McGee, 2025, p. 113).

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 US innovation rate under the baseline and the counterfactual (JV ban in 1999). Panel B plots the US innovation rate in the baseline as a function of the US–China leader technology gap m^F, evaluated in 2025. $m^F > 0$ denotes the case where US leaders have higher productivity than Chinese leaders. In Panel B, the technology gaps between domestic firms are set to $m^{DF} = m^{DH} = \bar{m}$.

Table 7: Baseline vs. Ban of Joint Venture Investments in 1999

	Baseline	Ban on 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

Notes. This table reports net present values of real profits and labor income, deflated by the US price index and normalized by baseline total real income, under the counterfactual that JVs are banned from 1999 onward versus the baseline. Leader profits include own profits, JV profits, and JV fees.

demand, wages, and prices—arises from leader firms' failure to internalize fringe firms' profits. This GE response is not an independent channel; it is the aggregate consequence of this within-product failure compounding across all products. We confirm this in the next subsection: when leaders internalize fringe profits, fewer JVs are established and the real wage decreases following a JV ban.

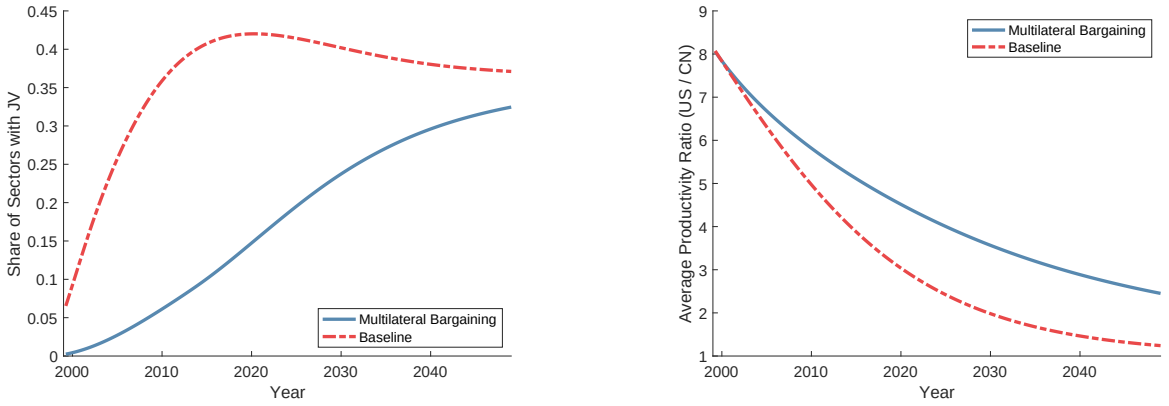
In contrast, both leader and fringe profits decline in China because of reduced diffusion, and labor income also falls as labor demand weakens (see Appendix Table D1 for the China decomposition). Slower diffusion also pushes price levels higher in China.

To further examine the mechanisms and the robustness of these results, we consider alternative modeling assumptions, reported in Appendix Table D3. When we shut down the innovation channel by setting the R&D cost parameter to infinity, the JV restriction still raises US welfare by 0.39%, though the magnitude is 68% smaller than the baseline (0.39% vs. 1.20%). Without innovation, JVs become the only source of productivity improvement for Chinese firms beyond exogenous diffusion, generating larger welfare losses for China. This implies that innovation responses to JVs play an important role in the welfare effects. We also consider preserving love-of-variety effects instead of shutting them down. Because JVs introduce additional varieties, the welfare gains from restricting JVs become smaller from this love-of-variety loss, but they remain positive at 0.73%. Finally, we consider constant markups as in standard monopolistic competition, and the results remain robust. Overall, the US welfare gains from restricting JVs are robust to these alternative modeling assumptions. Sensitivity checks with respect to key parameters (ϕ, δ^F, δ^D, $\mathcal{D}$, and κ) also confirm robustness (Appendix Table D4).

6.2 What is the Key Market Failure in JV Decisions?

We showed that there can be over-investment in JV, which lowers US welfare relative to the JV-ban counterfactual. To further illustrate that such over-investment arises because US leaders do not internalize fringe profits, we consider coordinated JV decisions: a JV can only be established if US leaders compensate fringe firms for their future losses (i.e., leaders internalize fringe profits). More specifically, we add an additional bargaining problem between US leaders and fringe firms, in addition to the one between US and Chinese leaders (see Appendix D.2 for details). As a result, a JV is established only when the total surplus to US leader and fringe firms is positive. 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.

Figure 4: Coordinated Joint Venture Decisions: Baseline vs. Multilateral Bargaining



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 China (Panel B) in the baseline and in the counterfactual with coordinated JV decisions (equation 6.1), in which US leaders compensate domestic fringe firms for JV-related profit losses through multilateral bargaining.

The modified bargaining outcomes are:

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

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

Coordinated JV decisions raise US welfare by 1.7% relative to the uncoordinated baseline. By requiring US leaders to compensate their own fringe firms, coordination makes JVs more costly for US leaders and better aligns US leaders' interests with the social welfare criterion. As Panel A of Figure 4 shows, fewer JVs are formed under coordination. With fewer JVs, technology diffusion to China slows and China's convergence rate declines (Panel B).

Coordination therefore alters the welfare impact of banning JVs. A JV ban from 1999 onward decreases US welfare by 0.6% and Chinese welfare by 2.0% (col. 2 of Table 6). Because

coordination already aligns US leaders' interests with the social welfare criterion, a JV ban no longer raises US welfare but instead lowers it. For China, the ban has a smaller negative effect under coordination because fewer JVs exist and less technology diffuses through them.

We also decompose US welfare by income source, as in Table 7 (Appendix Table D2). Under multilateral bargaining, all income sources—leader profit, fringe profit, and importantly real wage—decrease when JVs are banned. This confirms that the large general-equilibrium response under the uncoordinated baseline was itself a consequence of leader firms failing to internalize fringe firms' profits. When this failure is removed via coordination, the real wage channel reverses sign.

6.3 Quid-Pro-Quo Policy

Another important question is how the elimination of China's quid-pro-quo policy, which mandates direct technology transfer through JVs, affects US and Chinese welfare. We interpret the direct diffusion parameter ϕ as the counterpart of the quid-pro-quo policy: ϕ captures the additional rate of diffusion from US to Chinese leaders triggered by JV formation, on top of within- and cross-country diffusion. Setting $\phi = 0$ therefore isolates the mandated technology-transfer component of the policy.

Relative to the baseline with $\phi = 0.13$, US welfare rises by 3.2% and Chinese welfare falls by 5.3%. The direction of the welfare effects is consistent with Holmes et al. (2015), who find that the quid-pro-quo policy benefits China but hurts the US. Our China welfare magnitude (5.3%) is comparable to the 4.69% reported by Holmes et al. (2015), but our US welfare gain (3.2%) is substantially larger than their 0.45%. The larger US effect arises from strategic interaction in joint-venture and innovation decisions, absent in their model.

6.4 Comparative Advantage

JVs are more likely to be established in industries with larger technology gaps (see the non-targeted moment in Table 5). In other words, JVs are more likely to form where the US initially holds a large comparative advantage. This selection arises because the total JV surplus—split between the two leaders—is higher when the US-China gap is larger. As a result, technological diffusion through JVs directs China's productivity growth toward industries in which the US

initially holds a large comparative advantage, eroding US comparative advantage over time.

Well-known theoretical results (Dornbusch et al., 1977; Samuelson, 2004) show that US welfare gains from trade can decline when China's productivity grows in a way that diminishes US comparative advantage. To explore this, we compare static gains from trade in the baseline and the JV-ban counterfactual, holding productivity distribution constant in autarky to the open economy levels.[45] Consistent with the theoretical results, US gains from trade are 3.9% in the baseline and rise to 4.2% under the JV restriction. JVs therefore hurt US welfare partly by eroding US comparative advantage. This is another reason why JVs lead to a lower US real wage.

6.5 What if the US Bans Joint Venture Investments in 2025?

Next, in light of recent policy debates, we consider restricting JVs in 2025 rather than 1999. In contrast to the 1999 case, banning all JVs starting in 2025 reduces (rather than raises) US welfare by 0.7% (col. 4 of Table 6, measured in 2025). By 2025, the US-China technology gap has narrowed substantially (Appendix Figure D3), so technology diffusion and the resulting competition effect on US fringe firms have weakened. Although the ban still slightly widens the US-China productivity gap, the forgone JV profits and lost market access outweigh the modest gains from reduced technology diffusion. Overall, the welfare gains from a JV ban decline over time as the US-China productivity gap narrows (Appendix Figure D2), implying that the timing of the ban determines its welfare consequence.

6.6 Joint Venture Restriction Conditional on Technology Gaps

Next, we consider a state-dependent restriction that bans JVs only when the US-China productivity gap is larger than a certain threshold, to slow down technology diffusion in industries where the US has a large 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

[45] Specifically, we make firms choose the same innovation and JV rates as in the open economy. Then, when we move to autarky, we let this choices the same, so that productivity distributions are the same. The reason we are doing here is our focus is static gains from trade rather than dynamic effects of opening up to trade on innovation and JV decisions. Focusing on static gains from trade is also conceptually align with the theoretical results by Dornbusch et al. (1977) and Samuelson (2004). Also, see di Giovanni et al. (2014) and Liu et al. (2024) for quantitative analyses of biased growth based on static trade models.

gives the largest welfare gains among such state-dependent JV restrictions. The policy can be viewed as an effort to maintain US comparative advantage in high-tech sectors. Under this policy, US welfare rises by 1.33% relative to the baseline (col. 3 of Table 6), which means that it delivers a higher level of welfare than the policy that restricts all JVs regardless of the US-China productivity gap (welfare gain of 1.20%). However, this policy has the unintended consequence of weakening US leaders' innovation incentives, as it reduces their value of maintaining $m^F \geq 6$.

6.7 Policy Cooperation, Discount Rate, and Political Economy

So far, we have assumed that China's policy does not respond to the US actions. We now consider China's retaliation against the JV ban by subsidizing labor in tradable sectors for both production and R&D. The policy space of US is whether to ban JVs, and China's policy space is the level of labor subsidy.[46] Then, we compute the Nash equilibrium in these two policy spaces, which is the intersection of the best responses of the two governments.[47] The Nash equilibrium is that the US bans JVs and China provides a 20% subsidy. This yields a US welfare gain of 0.22% and a Chinese welfare loss of 9.65%, both relative to the status-quo baseline with JVs. In this Nash equilibrium, in the current calibration, banning JVs remains optimal for the US regardless of China's reaction, although the positive effects of the JV ban decrease from 1.20% to 0.22% due to the retaliation.

We next consider policy coordination, in which the two countries jointly maximize total surplus through symmetric Nash bargaining, taking the Nash equilibrium as the threat point and allowing international transfers as in Ossa (2014). The global gains from policy

[46] We also considered the US taxing joint venture profits, instead of making two discrete cases. But, in the current calibration, we find that shutting down always increases US welfare by more than any level of tax. For China's subsidies, we incorporate a deadweight loss parameter υ, such that the Chinese government must raise $1+\upsilon$ dollars in taxes to finance one dollar of spending, following Feldstein (1999). Without these deadweight costs, we found that it is optimal for the Chinese government to subsidize labor excessively due to externalities related to innovation. Having some deadweight costs makes the counterfactual more interesting. Also, this is consistent with empirical evidence that China's subsidies are wasted, for example, due to just relabeling administrative costs as R&D costs as shown by Chen et al. (2021).

[47] Specifically, the US and Chinese governments maximize their household welfare taking the other country's policy as given: $\max_{D^{\text{ban}} \in \{0,1\}} U_{\text{US},99}(D^{\text{ban}}; \tau^{\text{CN},w})$ for the US, and $\max_{\tau^{\text{CN},w} \in [0,\infty)} U_{\text{CN},99}(\tau^{\text{CN},w}; D^{\text{ban}})$ for China, where $U_{\text{US},99}$ and $U_{\text{CN},99}$ are each country's household discounted utility in 1999, D^{ban} is an indicator of the JV ban and $\tau^{\text{CN},w}$ is China's subsidy rate.

coordination are split equally between the two countries.[48] Under coordination, the US does not ban JVs and China does not subsidize, which yields a welfare increase of 5.71% in both countries relative to the Nash equilibrium.

In the analysis above, we assume the US government shares the discount rate of the US representative household. However, it may apply a higher discount rate—placing more weight on short-run effects than on long-run consequences—because of, for example, four-year election cycles. As Figure 2 shows, the positive welfare gain reflects the long-run gains outweighing the short-run losses. We therefore solve for the threshold discount rate at which the social planner becomes indifferent between banning JVs and the no-ban baseline.[49] We find that planners with discount rates above 5.82% (94% higher than the baseline value $\rho = 0.03$) prefer not to ban JVs.

A related consideration is political economy. The US government may place additional weight on leaders' profits, for example, because of lobbying. We adopt the political-economy formulation of Ossa (2014), building on Grossman and Helpman (1994): the US policymaker maximizes a politically-adjusted welfare objective $(1 - \Lambda)(1 + \omega) + \Lambda\hat{\Pi}_h$, where ω is the consumption-equivalent household welfare gain, $\hat{\Pi}_h$ is total US leaders' present-discounted profits, and Λ is the relative weight on leader profits. Because US leaders lose profits under the JV ban (Table 7), a higher Λ tilts the US government against the ban. We find that the US government chooses not to ban JVs whenever $\Lambda \geq 0.048$.

7. Conclusion

The intensifying economic and geopolitical rivalry between the United States and China has spurred ongoing debates over whether US firms transfer too much technology to China and if policies should be implemented to curb such transfers. Our oligopolistic competition model with innovation and technology diffusion provides a justification for policy interventions, demonstrating that leading US firms may over-invest in joint ventures in China. This is because they do not account for the negative competition effects on other US firms or the

[48] Specifically, we solve $\max_{\{D^{\text{ban}}, \tau^{\text{CN},w}, \Delta\}} \frac{U_{H,99}}{U_{H,99}^{\text{Nash}}}$ subject to $\frac{U_{H,99}}{U_{H,99}^{\text{Nash}}} = \frac{U_{F,99}}{U_{F,99}^{\text{Nash}}}$, where $U_{H,99}^{\text{Nash}}$ and $U_{F,99}^{\text{Nash}}$ are each country's utility under the Nash equilibrium, and Δ is the international transfer from China to the US. The transfer redistributes the global gains from policy coordination.

[49] Specifically, we calculate ω from equation (4.11) under alternative values of ρ.

general equilibrium effects that reduce the real wage. Despite this seemingly straightforward economic logic, this specific mechanism has not been formally explored in the literature.

Our findings show that a complete ban on joint ventures beginning in 1999 would have raised US welfare. However, we also identify alternative policies that could generate even greater welfare gains, such as mandating that leaders compensate fringe firms for future profit losses, restricting joint ventures in industries with particularly large US-China productivity gaps, or policy cooperating with China. While these policies may be challenging to implement and enforce, they highlight the specific market inefficiency at play.

Furthermore, our research does not suggest that banning joint ventures will always improve US welfare. By 2025, the US-China technology gap is small enough that restricting joint ventures would actually reduce US welfare. This finding underscores the importance of a dynamic approach to policy, as the effectiveness of any intervention is highly dependent on the current economic and technological context.

Our analysis serves as a useful first step and broaches several avenues for future research. On the empirical side, our novel findings on the direct and indirect effects of joint ventures on Chinese and US firms could be refined to better understand the role of firm heterogeneity. For instance, future work could examine how the characteristics of different US leader firms, such as their size or R&D intensity, influence their joint venture decisions and the extent of technology leakage. Similarly, it would be valuable to explore how the absorptive capacities of Chinese firms affect their ability to benefit from spillovers. In addition, future research could explore alternative measures and methodologies to better identify the causal effects of technology transfer through joint ventures.

On the modeling side, we do not separately model other forms of FDI, such as acquisitions or WFOEs, or licensing contracts, all of which also facilitate between-country technology diffusion. While the underlying mechanism may be qualitatively similar, it would be a valuable extension to quantitatively assess the roles of these alternative channels of technology transfer.

Another compelling avenue for future research is to explore the interaction between optimal tariffs and joint venture policies, as tariffs can attenuate the negative competition effects on US firms from joint ventures and technology diffusion to Chinese firms. This is a direction we are currently pursuing in other ongoing work.

Finally, a three-country model that includes China and two advanced countries (for example, the US and Japan) would allow for the analysis of strategic interactions between the leader firms of the advanced nations. This framework would likely reveal a prisoner's dilemma-like dynamic, where each firm's unilateral incentive to form joint ventures in China results in a collectively suboptimal outcome of excessive technology leakage. Such a model could also be used to explore the strategic interactions between the two advanced country governments regarding joint venture policies. This is a promising avenue for our future research.

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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 B6—we apply the same cleaning procedure as for US Compustat. We follow Autor et al. (2013) and aggregate these codes up to 383 4-digit codes for compatibility with the CIC and HS codes.

Sectoral data. We map Compustat data to Comtrade and the NBER-CES database using industry codes. Comtrade data, obtained from BACI (Gaulier and Zignago, 2012), are converted from HS 6-digit codes to 1987 SIC 4-digit codes following Pierce and Schott (2012). We obtain the SIC 4-digit level NTRgap_j from Che et al. (2022).

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

We construct the concordance between the 4-digit Chinese Industrial Classification (CIC) and 1987 SIC codes in two steps. First, we map CIC 2002 to NAICS 1997 using the concordance table from Ma et al. (2014), and then apply the 1997 NAICS to 1987 SIC concordance from the US Census. Each unique 4-digit CIC code maps to multiple 4-digit 1987 SIC codes; for these multi-mappings, we assign weights based on 1995 gross output from the NBER-CES Manufacturing Industry Database, so that larger industries receive greater weight.

Second, using this mapping, we construct the JV exposure at the 4-digit SIC level. The denominator of the JV exposure in equation (3.4) is Total sales$_{j,98} = \sum_{h \in \text{CIC}(j)} \omega_h^j \sum_{g \in \mathcal{F}_{h,98}} \text{Sale}_{gh,98}$, where $\mathcal{F}_{h,98}$ is the set of firms with CIC code h in 1998, CIC(j) is the set of 4-digit CIC codes mapped to SIC j, and ω_h^j is the weight assigned to CIC h within SIC j. The numerator is computed analogously over JV affiliates:

$$\Delta\text{JV domestic sales}_j = \sum_{h \in \text{CIC}(j)} \omega_h^j \left(\sum_{g \in \mathcal{J}_{h,12}} \text{Sale}_{gh,12}^{\text{dom}} - \sum_{g \in \mathcal{J}_{h,99}} \text{Sale}_{gh,99}^{\text{dom}} \right),$$

where $\mathcal{J}_{h,t}$ is the set of JV affiliates with CIC code h in year t. We use this 4-digit SIC JV exposure for the regression in Table 2. We proceed analogously for the WFOE exposure in equation (3.5). For the regression in Table 1, we aggregate back to the 4-digit CIC level: $\Delta\text{JV}_h = \sum_{j \in \text{SIC}(h)} \omega_j^h \Delta\text{JV domestic sales}_j$, where ω_j^h is the weight assigned to SIC j within CIC h when CIC h maps 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.

Unlike the OLS regressions in equation (3.3), we focus on total FDI rather than separating

JVs and WFOEs. because our IV strategies, detailed below, exploit exogenous variation in total FDI rather than JV and WFOE separately. Therefore, we focus on the combined effects and run the following specification, analogous to equation (3.3):

$$\Delta y_{fj} = \beta_1 \Delta \text{FDI}_{fj} + \vartheta \text{NTRgap}_j + \mathbf{X}'_{fj}\gamma + \varepsilon_{fj}, \tag{B.1}$$

where the FDI expoosure is defined analogously to the JV and WFOE exposures (equations (3.4) and (3.5)):

$$\Delta \text{FDI}_{fj} = \frac{\Delta \text{FDI dom. sales}_{fj}}{\text{Total sales}_{j,98}} = \frac{\sum_{g \in \mathcal{J}_{(-f)j,12} \cup \mathcal{W}_{(-f)j,12}} \text{Sales}^{\text{dom}}_{gj,12} - \sum_{g \in \mathcal{J}_{(-f)j,99} \cup \mathcal{W}_{(-f)j,99}} \text{Sales}^{\text{dom}}_{gj,99}}{\text{Total sales}_{j,98}}, \tag{B.2}$$

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 Korea, relative to China's total sector sales in 1998:

$$\text{IV}^{\text{JP-KR}}_j = \frac{\Delta \text{India FDI (S. Korea \& Japan) sales}_{jt}}{\text{Total sales}_{j,98}} = \frac{\sum_{g \in \mathcal{J}^{\text{IN,JP-KR}}_{j,12}} \text{Sale}_{gj,12} - \sum_{g \in \mathcal{J}^{\text{IN,JP-KR}}_{j,99}} \text{Sale}_{gj,99}}{\text{Total sales}_{j,98}}, \tag{B.3}$$

$\mathcal{J}^{\text{IN,JP-KR}}_{jt}$ is the set of FDI affiliates in India associated with MNEs from South Korea or Japan. 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 South Korea or Japan 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 South Korea and Japan because they were the two largest sources of FDI in China.

Second IV Strategy. We also consider a second IV strategy, where we instrument the FDI exposure with domestic Chinese FDI policy change based on the Catalogue, proposed by 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 industries more attractive for FDI, potentially correlating FDI by MNEs in the US, South Korea, or Japan. 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 pretrends and industry-level balance, following Borusyak et al. (2022), reported in Appendix Table B8. First, pre-1999 5 year growth (1993-1998) is not meaningfully correlated with the IV. Overall imports (excluding China, India, Japan, and Korea), and imports from China do not show any pretrends. 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 B9).[50]

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

[50]Since Chinese firm data is only available after 1998, we are unable to assess their pretrends.

industry characteristics that could be related to unobserved shocks. The export platform is unlikely to be a significant concern, as there is no significant correlations between bilateral import penetration (import-to-domestic absorption ratio) and the IV for China, India, and the US. Moreover, sectors with higher IVs are not necessarily those in which China initially had higher productivity or those more exposed to FDI, supported by the lack of correlation between the IV and Chinese import penetration in the US, FDI affiliates' initial sales shares in China, or their numbers relative to the total firm numbers. While our research design does not require industries 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 from China, India, Japan, and 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 pretrends in gross output or employment, which we do not observe. Also, including them as additional controls leaves our estimates unchanged, suggesting that omited variable bias due to these unobservables is unlikely to be a major concern.

Finally, productivity improvements in India, Japan, and Korea, three countries used for our IV construction, could increase Japanese and Korean FDI into India and at the same time negatively affect US firms through direct import competition. To alleviate this concern, we control for changes in US import shares from these three countries over 1999–2012. Because these import shares may themselves be endogenous, we instead use predicted import shares based on each country's imports from all other countries (excluding the three countries, the US, and China) following Hummels et al. (2014). Our estimates remain stable to these controls. Moreover, if endogeneity through import competition is a significant concern, our estimate for Fact 3 would likely be overstated, while our estimate for Fact 2 would be understated.

However, we find no evidence of underestimation for Fact 2. In fact, the IV estimates for Fact 2 are larger than the OLS estimates, alleviating this concern.

Estimation Results. Table B10 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 and changes in predicted import shares from South Korea, Japan, and India.

B.3 Additional Evidence on Indirect Spillovers

In this subsection, we present additional evidence on indirect technology 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 group MNEs that did not form any JVs.

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

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

$$y_{imt} = \sum_{\tau=-5}^{5} \beta_\tau \left(D_{mt}^{\tau} \times \mathbb{1}[\text{JV Formation}_{imt}] \right) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}, \tag{B.4}$$

where $\mathbb{1}[\text{JV Formation}_{imt}]$ is a dummy of forming JVs, and D_{mt}^{τ} is 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 technology diffusion, we expect non-partner firms to increase citations because their technologies may build upon the technology diffused from MNEs.

Figure B3 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 technology diffusion, but rather because the MNEs involved in the JV experienced innovation or productivity shocks, which made their patents more likely to be cited. 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

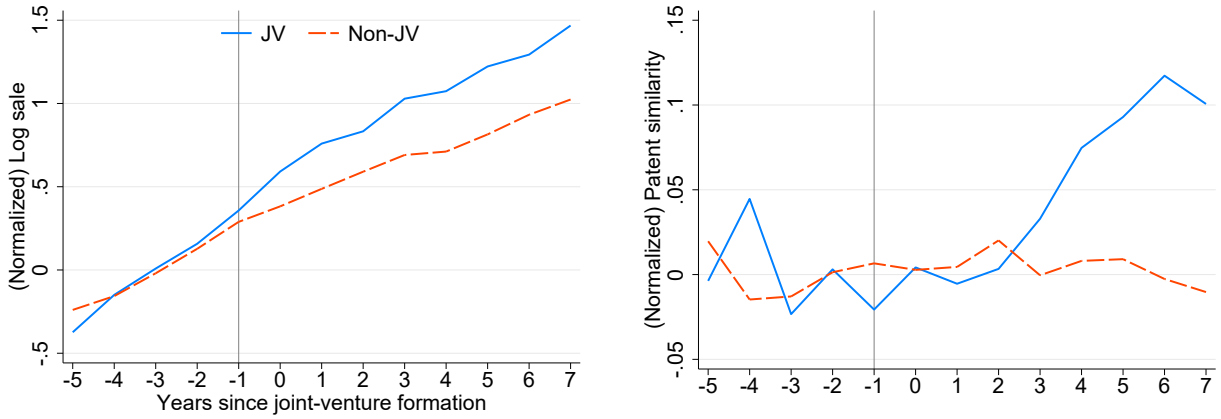
Notes. This table presents descriptive statistics for treated and control firms from five to one years before the event. Column 9 reports t-statistics for the mean differences between winners and losers, while Column 10 provides the corresponding p-values (in brackets), computed using standard errors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

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

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

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

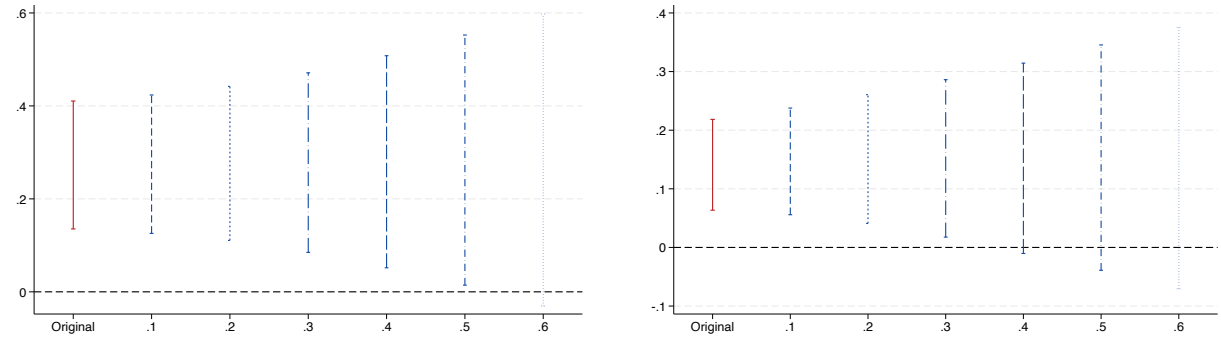
Figure B1: Raw Plots. Direct Effects of Joint Venture Formation on Chinese Partner Firms



A. Log sales B. Technological proximity

Notes. The figure plots mean trends of log sales and technological proximity (equation (3.2)) for treated and control groups, residualized on match fixed effects. All values are normalized by each group's pre-event average.

Figure B2: Robustness. Sensitivity to Violations of the Parallel Trend Assumption. Direct Effects of Joint Venture Formation on Chinese Partner Firms



A. Log sales B. Tech. proximity

Notes. This figure presents results of the sensitivity checks for potential violations of the parallel trend assumption based on Rambachan and Roth (2023). The figure reports the estimated 90% confidence intervals, based on standard errors two-way clustered at the firm and match levels, for β_4 of equation (3.1) over different values of M which is a parameter that governs magnitude of violations to the parallel trend assumption: $\Delta^{RM}(M) = \{\delta : \forall t \geq 0, |\delta_{t+1} - \delta_t| \leq M \times \max_{s \leq 0} |\delta_{s+1} - \delta_s|$, where $\max_{s \leq 0} |\delta_{s+1} - \delta_s|$ is the maximum pre-treatment violation of parallel trends. $M = 1$ is a natural benchmark, which bounds the worst-case post-treatment difference in trends by the maximum in pre-treatment periods (Rambachan and Roth, 2023, p.2563). β_{-1} is normalized to zero. In Panels A and B, the dependent variables are log sales and technological proximity (equation 3.2).

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

	Baseline outcomes			Alternative outcomes				
Dep. var.	Log sales	Ihs export	Technological proximity	Log capital	Log emp.	Dum. export	Ihs patent stock	Ihs annual patent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5 years before	−0.03	0.78	0.03	0.02	−0.01	0.07	−0.12	−0.13
	(0.10)	(0.77)	(0.06)	(0.11)	(0.12)	(0.05)	(0.16)	(0.17)
4 years before	−0.02	0.07	0.06	−0.04	0.04	0.00	0.01	0.12
	(0.08)	(0.61)	(0.04)	(0.09)	(0.09)	(0.04)	(0.12)	(0.12)
3 years before	0.03	0.36	0.03	−0.05	0.02	0.02	0.01	0.06
	(0.05)	(0.56)	(0.03)	(0.09)	(0.08)	(0.04)	(0.10)	(0.11)
2 years before	−0.01	0.23	0.04	0.06	−0.00	0.01	−0.02	0.01
	(0.04)	(0.44)	(0.03)	(0.06)	(0.05)	(0.03)	(0.06)	(0.08)
1 year before								
Year of the event	0.13***	0.14	0.02	0.11**	0.04	−0.00	0.04	0.12
	(0.04)	(0.35)	(0.03)	(0.05)	(0.04)	(0.03)	(0.04)	(0.08)
1 year after	0.16***	0.20	0.02	0.16***	0.14**	0.01	0.14*	0.17*
	(0.05)	(0.48)	(0.03)	(0.05)	(0.06)	(0.03)	(0.08)	(0.10)
2 years after	0.13*	0.62	0.05	0.25***	0.12	0.04	0.25**	0.25**
	(0.07)	(0.58)	(0.04)	(0.07)	(0.09)	(0.04)	(0.11)	(0.12)
3 years after	0.22***	1.09*	0.12**	0.31***	0.07	0.05	0.30**	0.35***
	(0.08)	(0.56)	(0.05)	(0.08)	(0.11)	(0.04)	(0.12)	(0.12)
4 years after	0.27***	1.01*	0.14***	0.35***	0.14*	0.06	0.44***	0.47***
	(0.08)	(0.57)	(0.05)	(0.08)	(0.09)	(0.04)	(0.14)	(0.14)
5 years after	0.32***	1.29*	0.14***	0.37***	0.05	0.08*	0.43***	0.37***
	(0.10)	(0.68)	(0.05)	(0.09)	(0.13)	(0.05)	(0.15)	(0.14)
6 years after	0.38***	1.24	0.15***	0.43***	0.07	0.06	0.55***	0.62***
	(0.11)	(0.83)	(0.05)	(0.10)	(0.15)	(0.05)	(0.16)	(0.17)
7 years after	0.46***	1.12	0.15***	0.54***	0.15	0.09*	0.45**	0.40**
	(0.11)	(0.85)	(0.06)	(0.12)	(0.15)	(0.05)	(0.19)	(0.19)
Fixed effects	Firm-match, Match-year							
Mean dep. var.	17.77	10.39	0.22	16.44	6.48	0.58	0.95	0.62
# Cluster (match)	176	176	106	176	176	176	176	176
# Cluster (firm)	859	859	321	859	859	859	859	859
N	7457	7457	1746	7457	7457	7457	7457	7457

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. The dependent variables are log sales (col. 1), the inverse hyperbolic sine of exports (col. 2), technological proximity from equation (3.2) (col. 3), log capital (col. 4), log employment (col. 5), an export dummy (col. 6), and the inverse hyperbolic sine of cumulative patent stock (col. 7) and of yearly new patents (col. 8). All specifications include match-firm and match-year fixed effects. In column 3, the sample size decreases because technological proximity is only well-defined for firms with positive patent stock in both the treated and control groups.

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

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

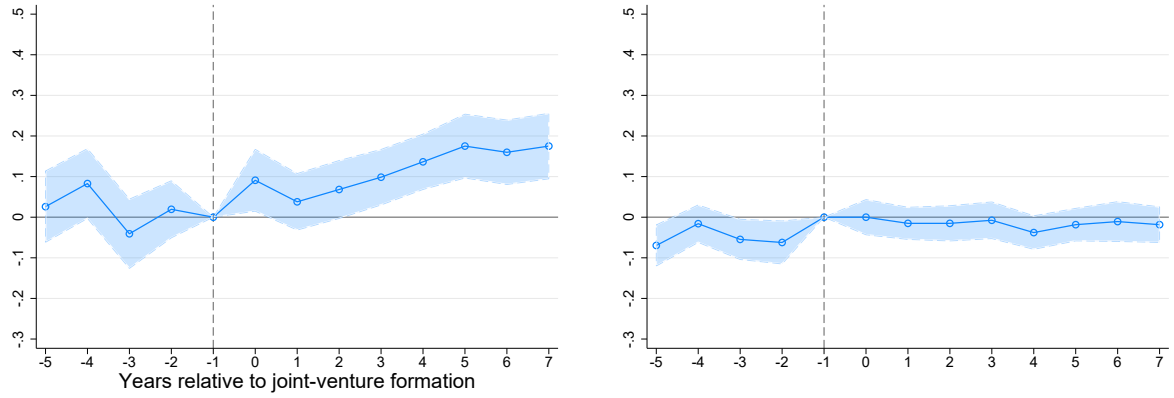
Notes. Standard errors, shown in parentheses, are clustered at the match and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimated event study coefficients of equation (3.1). β_{-1} is normalized to zero. In columns 1–3 and 4–9, the dependent variables are log sales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

Table B5: Evidence of Productivity Upgrading of Chinese Firms (OLS)

Dep. var.	Δ # export prod	Δ # export cty	ΔWage per emp	Dum. gvnt high-tech
	(1)	(2)	(3)	(4)
ΔJV_{fj}	25.25***	24.53***	3.49***	6.39***
	(4.16)	(4.42)	(1.05)	(0.58)
$\Delta WFOE_{fj}$	−10.98	−4.02	−3.44	5.13
	(12.80)	(11.85)	(2.95)	(3.16)
$NTRgap_j$	1.62***	1.45***	0.07	−0.07
	(0.42)	(0.45)	(0.14)	(0.09)
# clusters	152	152	156	156
N	4972	4972	11959	11978

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 OLS estimates of equation (3.3). ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). In columns 1–4, the dependent variables are the DHS growth of the numbers of exporting products/countries over 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 the tariff increase on Chinese goods from a failed NTR renewal. All specifications include dummies of state-owned firms. All regression models are weighted by initial sales.

Figure B3: 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.4). 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 B6: Negative Outcomes for Global Firms (OLS)

Dep. var.	ΔSale			ΔEmp			ΔCapital			ΔR&D		
Sample	All	High GDP	Low GDP	All	High GDP	Low GDP	All	High GDP	Low GDP	All	High GDP	Low GDP
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
ΔJV_j	−11.17***	−6.57*	−16.46***	−2.63**	−1.48	3.92	−10.46***	−8.75***	−12.10***	−11.30***	−9.37***	−43.30***
	(3.22)	(3.60)	(4.05)	(1.28)	(1.52)	(2.89)	(2.15)	(2.79)	(3.62)	(2.51)	(2.50)	(9.17)
$\Delta WFOE_j$	5.72	4.49	0.92	10.30*	7.76	19.98	9.27	8.48	10.55	6.97	4.87	38.03
	(5.64)	(6.14)	(8.96)	(5.38)	(6.09)	(16.70)	(6.20)	(6.77)	(10.73)	(7.81)	(8.16)	(31.46)
$NTRgap_j$	−1.86**	−0.80	−3.01***	−0.88**	−0.48	−1.76***	−1.07**	−0.65	−1.69***	−0.97	−0.50	−3.07*
	(0.82)	(0.87)	(0.57)	(0.37)	(0.41)	(0.55)	(0.46)	(0.63)	(0.50)	(0.86)	(0.87)	(1.60)
Mean dep. var.	7.04	−7.61	51.11	−1.67	−5.05	10.48	−13.90	−22.94	14.14	1.23	−2.67	26.80
# clusters	112	107	83	107	102	76	111	105	82	74	63	40
N	928	616	312	692	494	198	858	571	287	303	214	89

Notes: Standard errors clustered at the SIC 3-digit level are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports OLS estimates of equation (3.3). The estimation sample includes global firms, excluding those from China and the US. ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). The dependent variables in columns 1–3, 4–6, 7–9, and 10–12 are DHS growth rates of sales, employment, capital, and R&D expenditure over 1999–2012. High-GDP countries comprise Western Europe, Canada, and Japan; low-GDP countries are the remaining countries. The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. The number of observations varies across outcomes because of missing data. All regressions are weighted by initial employment.

Table B7: Robustness. Positive Spillovers to Chinese Firms and Negative Outcomes for US Firms (OLS)

Robustness	Chinese firms: Positive spillovers				US firms: Negative competition			
	Alt. sample full-sample	Alt. clustering 4-digit level	Alt. sample period 1999–2007	Alt. weight emp.	Alt. sample full-sample	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: ΔSale							
ΔJV_{fj}	8.67***	7.93***	6.74	6.70***	−14.00***	−14.27***	−12.02**	−11.25***
	(1.41)	(1.77)	(6.34)	(1.43)	(2.34)	(2.64)	(4.91)	(2.78)
$\Delta WFOE_{fj}$	−2.82	0.77	32.30	1.97	8.51	9.07	9.77**	1.16
	(6.13)	(5.15)	(21.60)	(4.74)	(7.77)	(5.91)	(3.87)	(6.71)
[0.5em] Mean dep. var.	79.61	81.74	44.12	85.47	8.69	7.84	16.46	6.03
	Panel B. Dependent variable: ΔEmp							
ΔJV_{fj}	6.93***	3.98***	5.02	4.84***	−14.41***	−15.51***	−17.27***	−11.71***
	(1.23)	(1.52)	(5.60)	(1.09)	(2.72)	(3.05)	(3.08)	(3.63)
$\Delta WFOE_{fj}$	7.03	8.66	36.82***	6.63	16.02*	17.83**	14.72***	8.48
	(5.23)	(6.57)	(12.46)	(5.44)	(9.36)	(7.54)	(2.55)	(8.05)
Mean dep. var.	−7.08	−18.92	−16.90	−45.45	−10.82	−11.27	−1.78	−17.13
NTR gap ctrl.	✓	✓	✓	✓	✓	✓	✓	
# clusters	157	378	157	156	105	173	110	105
N	14844	11978	18326	11971	1017	949	1368	949

Notes: Standard errors are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. Standard errors are clustered at the CIC 3-digit level in columns 1–4 and 6–7, and at the CIC 4-digit level in column 5. This table reports OLS estimates of equation (3.3). ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). In Panels A and B, the dependent variables are the DHS growth rates of sales and employment for Chinese firms. Column 1 includes all FDI affiliates (JVs and WFOEs) among Chinese firms; column 5 includes all US firms that formed a JV or WFOE in China. In columns 1 and 5, the firm's own JV or WFOE affiliates are excluded from the construction of the JV and WFOE exposures. 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 alternative weights based on employment. Columns 1–4 include dummies for state-owned firms. Except in columns 4 and 8, regressions are weighted by initial sales.

Table B8: Pretrend and Shock Balance Test of the IVs

Balance variable	$IV_j^{JP,KR}$			IV_j^{pol}		
	Coef.	SE	p-val.	Coef.	SE	p-val.
Panel A. Pretrend						
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, KR) / 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, KR) / 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 level are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports OLS estimates obtained after regression industry-level characteristics on the IVs. 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 gross output.

Table B9: Firm-level Pretrend. Correlations between the IVs and Pre-1999 Firm Size Growth

	US firms DHS growth, 1993-1998			
Dep. var.	ΔSale	ΔEmp.	ΔCapital	ΔExport
	(1)	(2)	(3)	(4)
	Panel A. IV based on Korea & Japan's FDI in India			
$IV_j^{JP\text{-}KR}$	−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 level, 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 B10: Positive Spillovers to Chinese Firms and Negative Competition Effects to US Firms (IV)

Dep. var.	Chinese firms: Spillovers ΔSale		ΔEmp		US firms: Competition ΔSale		ΔEmp	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. IV based on 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 and SIC 3-digit levels in columns 1—4 and 5—8, respectively, are reported in parentheses. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the IV estimates of equation (3.3). ΔFDI_{fj} is defined in equations (**??**). 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 the tariff increase on Chinese goods from a failed NTR renewal. All specifications include dummies of state-owned firms. The even columns include 1996 US import penetration (overall imports, excluding US, China, India, Japan, and Korea, relative to domestic absorption), 1993 production worker shares, 1990 computer investment shares, 1-digit industry dummies, and changes in predicted import shares from South Korea, Japan, and India over 1999–2012. 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:

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

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

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

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

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

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

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:

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

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

Law of Motion for Productivity Gaps and JV Status. The law of motion for $\mu_t(\mathbf{m};\mathcal{J})$ is

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

The first four lines of the right hand side capture the mass that enters a state $(\mathbf{m};\mathcal{J})$ 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

To replicate the regression from the model, We simulate 100,000 products in the model, whose technology gap between US and China is randomly drawn from the calibrated initial

distribution. Since innovation and diffusion are stochastic, products become heterogeneous over time in terms of their technology gaps.

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. The time window spans five years before the treatment, defined as JV formation, to seven years after the treatment. 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. Therefore, β captures the treatment effect of JV formation to leaders, compared to the fring firms.

Industry-Level Regressions in Facts 2 and 3. To estimate the model, we replicate the industry-level regressions of facts 2 and 3 in Section 3. Each product corresponds to each industry. Specifically, 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 and j products. The dependent variable is DHS growth of US leaders' sales. $\delta_{m^F,99}$ are fixed effects for the initial US-China gap $m^F \in \{-\bar{m}, \ldots, \bar{m}\}$ in 1999. Multiple products with the same initial gap identify these fixed effects. We abstract away from additional controls used in the empirical analysis, because it is difficult to define the additional controls in the model (e.g., NTR gap).

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 over 1999–2012,

instead of the last value in 2012 due to mean reversion. In the model, JVs exit with an exogenous probability. Therefore, products (or industries) initially with JVs are likely to lose JVs due to exogenous exits by 2012, which leads to changes in JV sales shares over 1999–2012 that are negative due to this mean reversion. Despite the JV exits, however, Chinese firms in that sector may have already benefited from technology diffusion, increasing their market shares 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.

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

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

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

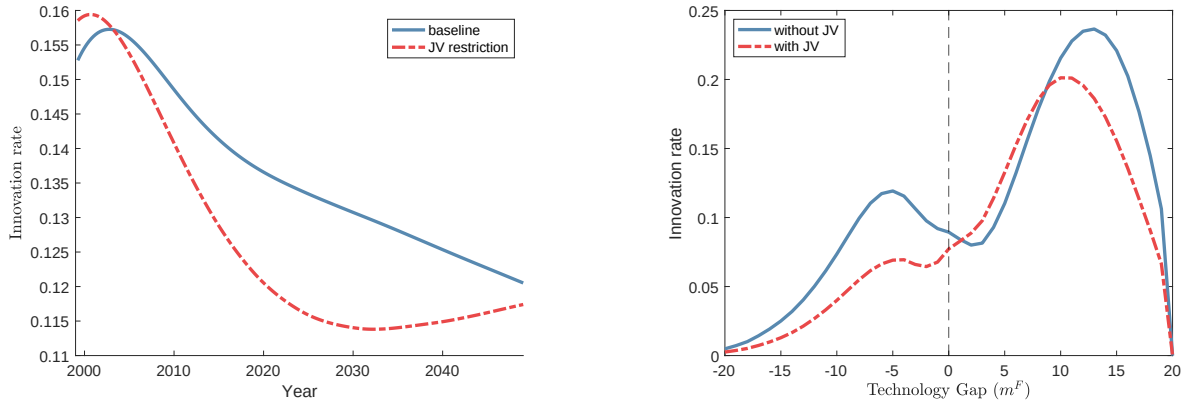
$$C = \frac{\xi^E(1-\xi)}{\xi^E(1-\xi)+\xi}\left\{\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \frac{\xi}{\xi^E(1-\xi)+\xi}\Delta^{\text{JV}} V_{ft}(\mathbf{m}) \tag{D.5}$$

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

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

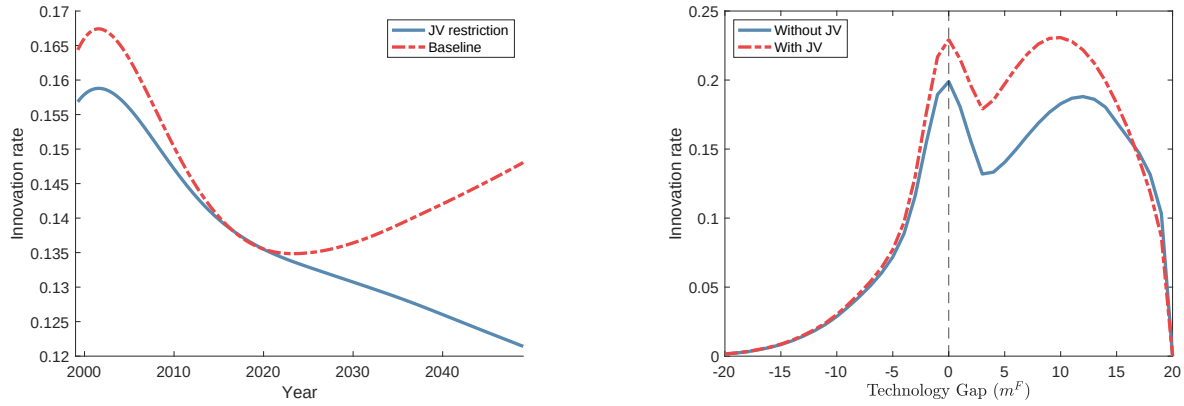
D.3 Additional Figures and Tables

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 Investments in 1999: Net Present Value of Real Profits and Labor Income. China

	Baseline	Shutting down JV	Changes (%)
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 D2: US Welfare Decomposition under Coordinated Joint Venture Decision: Baseline vs. JV Ban in 1999

	Baseline	JV Ban	Change (%)
US leader profit (own + JV + JV fee)	0.035	0.035	−0.12
Own profit	0.036	0.035	−2.14
JV profit	0.002	0.000	n/a
JV fee revenue	−0.003	0.000	n/a
US fringe profit	0.067	0.066	−1.74
US labor income	0.898	0.882	−1.74
US total real income	1.000	0.983	−1.69

Notes. This table reports net present values of real profits and labor income for the US, deflated by the US price index and normalized by total real income in the baseline with coordinated JV decision through multilateral bargaining in equation (6.1). The JV-ban counterfactual restricts new JVs from 1999 onward under the same coordinated-bargaining assumption. Leader profits include own profits, JV profits, and JV fees.

Table D3: 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

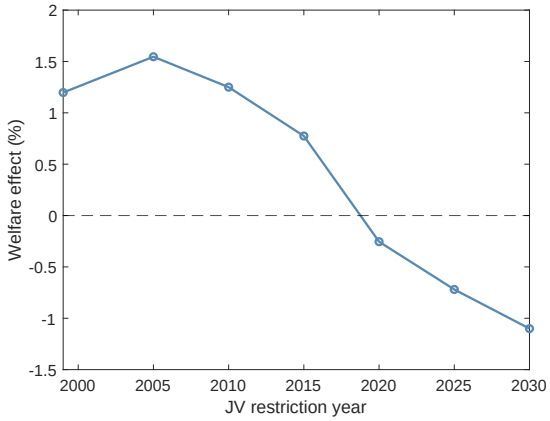
Notes. This table reports the effects of restricting JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

Table D4: 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 A. 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 B. 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 C. 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 D. 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 E. 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

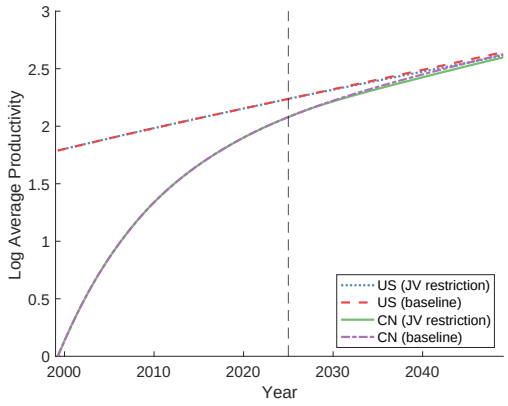
Notes. This table reports the effects of restricting JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

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

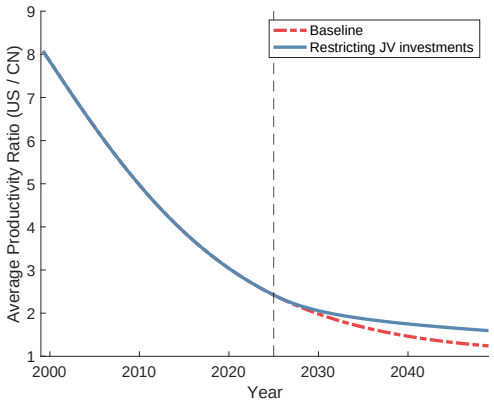


Notes. This figure reports consumption-equivalent welfare changes of the US from restricting JV investments in different years, compared to the baseline scenario. The x-axis denotes years in which JV investments begin to be restricted.

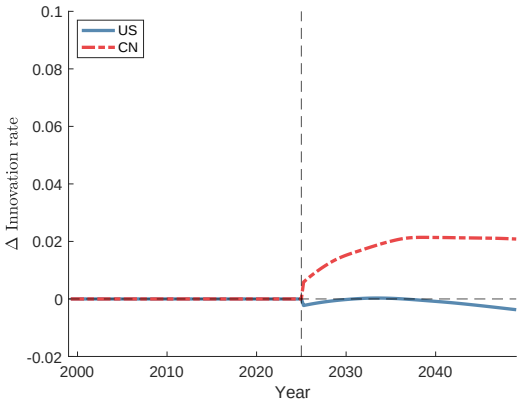
Figure D3: Baseline vs. Restricting Joint Venture Investments in 2025: Dynamics of Productivity, Innovation, and Consumption



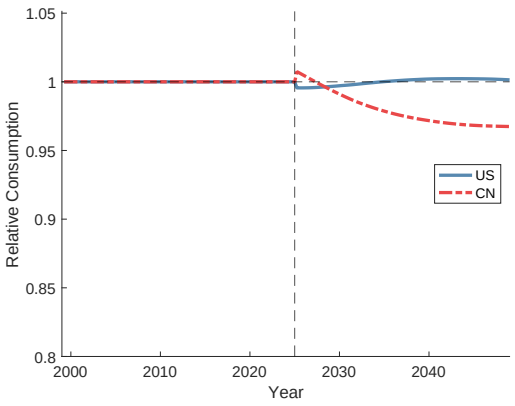
A. Log leader productivity



B. Productivity ratio (US/China)



C. Innovation rate difference



D. Relative consumption

Notes. This figure compares dynamics under the counterfactual (JV restriction beginning in 2025) to the baseline. The dashed vertical line is 2025. 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 (counterfactual over baseline).

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