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

Jaedo Choi
University of Texas at Austin

George Cui
International Monetary Fund

Younghun Shim
International Monetary Fund

Yongseok Shin
Hyundai Motor Group
Washington University in St. Louis

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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 partners, fueling future competition. While individual multinationals weigh the risks to their own profits, they disregard the negative impact on other US firms and the broader economy, resulting in an over-investment that may reduce US welfare. In our empirical analysis, across industries, US firms in those with more joint ventures in China experienced worse outcomes, and within industries, firms with greater product overlap with the participating multinationals declined more. 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 participating US firms at the expense of non-participants and the real wages of workers. A ban on joint ventures since 1999 would have boosted US welfare by 1.1 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, 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 main contribution is theoretical and quantitative. 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. The model is cali-

[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)

brated to micro data. Our quantitative analysis demonstrates that, from a US social welfare perspective, the market equilibrium leads to an excessive number of joint ventures.

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 two key motivating facts.

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

Second, and most importantly, we provide correlational evidence that joint ventures are associated with negative outcomes for non-participant US firms, both across and within industries. Across industries, US firms in those with more joint venture investment in China experienced larger declines in sales, employment, capital, and exports. Within industries, an event study around the first joint ventures shows that non-participants with greater product overlap with the participating US MNEs declined more. We find no such negative outcomes for wholly foreign-owned enterprises, which, unlike joint ventures, involve no local partners.

Motivated by these two facts, we build a simple model to highlight the business-stealing effect of joint ventures. There are two countries, the US and China. The US has a leader firm and a fringe firm, and China has a single firm that is initially less productive than both US firms. We model a joint venture as an agreement, reached through Nash bargaining, under which the US leader produces and sells in China without trade costs and in exchange shares its technology with the Chinese firm. Both parties gain, but the US fringe firm's profit falls. This is the business-stealing effect. We show that the joint venture reduces US welfare when this loss outweighs the consumer-surplus gain from lower prices.

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. We show that the welfare effect of

JV becomes negative when the demand factor for the US fringe firm is sufficiently large. In addition, the welfare effect of JV decreases with the foreign market size and the initial productivity gap.

For quantitative exploration of this business stealing effect, we develop a two-country growth model, 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 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 leaders 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 diffusion. The establishment of a joint venture in China introduces an additional probability of technology diffusion from the US leader firm to its Chinese counterpart, a feature consistent with our first fact. Consequently, the surplus from a joint venture includes not only the flow profit of the venture but also the value derived from the additional probability of diffusion to the Chinese leader firm.

The entry of a new joint venture firm immediately intensifies competition within the industry, and the stochastic diffusion of technology to the Chinese leader adds to this pressure over time. As in the simple model, the US leader accounts for these competition effects on its own profits when deciding whether to form a joint venture. Through bargaining, it also captures part of the joint venture's profit flow and of the diffusion benefits that accrue to the Chinese leader. The present discounted value of the US leader's profits is therefore higher with a joint venture—otherwise it would not form one. Fringe firms, by contrast, suffer a purely negative effect from intensified Chinese competition, consistent with our second fact. Because US leaders do not internalize this business-stealing effect, the equilibrium number of joint ventures may exceed the US social optimum.

We solve for the model's transitional dynamics, tracing the economy from an initial state in which Chinese firms are less productive than their US counterparts to a balanced growth path. We calibrate the model to match key empirical moments along this transition. We infer the parameters governing technology diffusion from the corresponding reduced-form regression coefficients in our empirical analysis. Importantly, the model reproduces our second fact, the negative outcomes for US firms, as a non-targeted moment. 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, which we confirm in the data as another non-targeted moment. As joint ventures shrink this gap through diffusion, they erode the US's comparative advantage and worsen its terms of trade, thereby reducing the gains from trade for the US.

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, 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.

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 US. 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 1.1 percent in units of permanent consumption. For the US, leaders' profits fall by 17 percent in present value terms, while fringe firms' profits rise by 6.3 percent. Although the total profit of the corporate sector declines, the real wage increases by 2.1 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 US 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 8.8 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 US.

To isolate the business stealing effect, we consider an alternative scenario in which US leader firms are required to compensate fringe firms for their losses from joint ventures. That is, US leaders are compelled to internalize the profit losses of their domestic competitors. With such multilateral bargaining, significantly fewer joint ventures are formed. Moreover, in this setting, a complete ban on joint ventures actually decreases US welfare. This indicates that the business stealing effect is a key source of the market inefficiency, and that coordinated joint venture decisions can deliver higher US welfare than an outright ban would.

In fact, our result does not imply that banning 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 technology diffusion 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.

Related literature. First, our paper contributes to the growth literature on innovation and trade 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; Rachapalli, 2021; Cai et al., 2022; Peters, 2022; Bai et al., 2025b,c; de Souza et al., 2025; Hémous et al., 2025; Milicevic et al., 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 technology diffusion. We extend this framework by incorporating the idea that multinational production facilitates technology diffusion from advanced to developing countries (e.g., Burstein and Monge-Naranjo, 2009; Holmes et al., 2015; Alviarez et al., 2023). Akcigit et al. (2024) discuss technology leakages in the context of Chinese venture capital investment in the US and national security concerns. Lam (2024) focuses on illegal imitation and studies optimal intellectual property rights protection in China. Santacreu (2025) studies dynamic effects of intellectual property rights provision. Our contribution lies in studying the business stealing effects of joint ventures through technology leakage, and in analyzing the policy implications both theoretically and quantitatively.

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 similar to innovation in our model. As in their analysis, technology leakage to China lowers multinationals' FDI incentives and reduces US welfare in our model. However, we differ in two main respects. First, our model focuses on the business stealing effect, absent in their framework. In their model, a representative firm maximizes its profit under perfect competition, so the firm's profit coincides with total sectoral (or aggregate) profit, which is not the case in ours. We find that once this externality is corrected for, the US can derive positive welfare from joint ventures even under the quid pro quo. Second, our model is calibrated on firm-level micro-data and our reduced-form estimates. Our empirical and quantitative analyses also suggest that this business stealing effect contributed to the recent US manufacturing decline (Autor et al., 2013; Acemoglu et al., 2016).

Regarding China's growth, Brandt et al. (2012) document sizable TFP growth using firm-level data. Alder et al. (2016) study place-based policy, and Brandt et al. (2017) trade liberalization. Song et al. (2011), Hsieh et al. (2015), Tombe and Zhu (2019), and Chen et al. (2021) study misallocation, and König et al. (2022) quantify its dynamic effects on TFP growth in an endogenous growth model. We instead study joint ventures as a key learning channel for

China's catch-up, consistent with recent micro-level evidence of positive spillovers from JVs (Jiang et al., 2024; Bai et al., 2025a). Among recent studies of US-China technology rivalry (e.g., Ju et al., 2024; Ma et al., 2025a,b; Alp and Ates, 2026), Ma and Zhang (2025) is closest. They document positive FDI spillovers in Chinese patent data and, using a Ricardian trade–multinationals–innovation model, find that the quid pro quo policy raised China's welfare. We study the US-side business stealing generated by the JVs that diffused technology into China and contributed to its growth.

This paper is also related to the large literature on multinationals (e.g., Helpman et al., 2004; Irarrazabal et al., 2013; Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018; Bilir and Morales, 2020; Garetto et al., 2024; Cai and Xiang, 2025). Many previous papers study the margin between exporting to foreign markets and establishing a foreign affiliate. Our contribution highlights a novel margin, the dynamic trade-off between market access and technology leakage.

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 tech-

nologies, 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. 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.[3]

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 obtain US firm outcomes from US Compustat that covers publicly listed firms, including sales, employment, and capital (measured as PPEGT). We also obtain each firm's

[3] 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).

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.[4] 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.[5]

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 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 and 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).[6]

We obtain sector-level 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 two motivating facts on joint ventures.

[4] 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.

[5] 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).

[6] 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.

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.[7] 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. The matching procedure yields 176 matches, involving 176 unique treated and 692 unique control firms. The treated and control groups are well-balanced across observables (Tables B3–B4).[8]

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

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

where i denotes firm, m match, and t year. D_{mt}^{τ} are event-time dummies. $\mathbb{1}[\text{JV Partner}_i]$ is an indicator for JV-forming firms. We normalize $\beta_{-1} = 0$. δ_{im} and δ_{mt} are match-firm and match-year fixed effects.[9] ε_{imt} is the error term. Standard errors are two-way clustered at the match and firm levels.

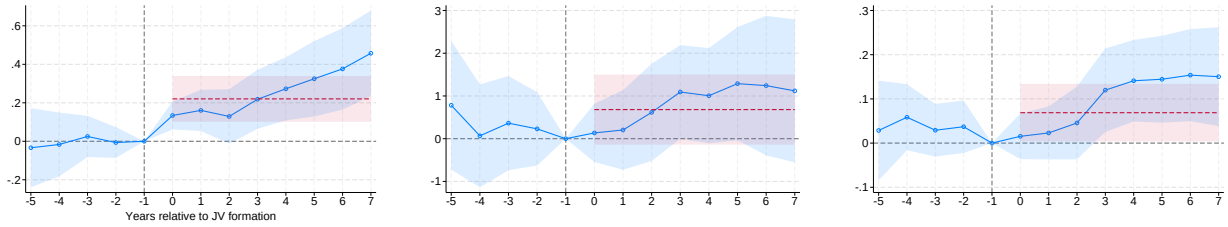
We consider three dependent variables, log sales, the inverse hyperbolic sine of exports, and technological proximity to foreign MNE partners. The first two capture firm size and performance in global markets. The last measures the extent to which Chinese partners became technologically similar to their foreign MNE partners after forming JVs. Following

[7] These observables are log sales, log capital, log employment, exporter and positive-patent-stock dummies, the inverse hyperbolic sines of exports and patent stock, and a state-owned enterprise (SOE) dummy. Larger firms and exporters are more likely to form a JV, and SOEs less likely (Figure B2).

[8] Figure B1 also shows that control-group sales follow the same trend before and after the event, while only treated-group sales rise after the event.

[9] 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. The red lines represent the average pooled diff-in-diff coefficients, with their 95% confidence intervals.

Bloom et al. (2013), we calculate technological proximity using patent data:[10]

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

$F_{imt} = (p_{i1t}, \ldots, p_{iKt})$ is a vector whose k-th element is Chinese firm i's patent stock (from the CNIPA) in the k-th technological field. $F_{\text{MNE}(m),t(m)}$ is the analogous vector for treated firm's foreign MNE partner of match m (from the USPTO), fixed at the event year $t(m)$.

Figure 1 reports the results. After forming JVs, Chinese partners' sales increased by 20% on average, and their export performance improved.[11] Furthermore, they became technologically closer to their foreign MNE counterparts. These findings suggest that their improved performance is related to technology transfer and diffusion from foreign MNE partners. These results are also consistent with Bai et al. (2025a), who find that Chinese partners' product strength resembled that of their foreign MNE partners in the auto industry.

Fact 2. Negative Outcomes for US Firms

Next, we examine how the rise in JV activity in China affects US firms.

[10]For the proximity measure to be well-defined, we require that both foreign MNEs and Chinese partners have engaged in patenting. We therefore restrict the sample to Chinese partners that ever patented in the Chinese patent system and foreign MNEs that ever patented at the USPTO.

[11]The average post-event effects (red lines) are obtained by running $y_{imt} = \beta(D_{mt}^{0\leq\tau\leq 7} \times \mathbb{1}[\text{JV Partner}_i]) + \sum_{\tau=-5}^{-2} \beta_\tau (D_{mt}^{\tau} \times \mathbb{1}[\text{JV Partner}_i]) + \delta_{im} + \delta_{mt} + \varepsilon_{imt}$, where $D_{mt}^{0\leq\tau\leq 7}$ is an indicator for $0 \leq \tau \leq 7$.

Across-Industry Evidence. We consider the following long-difference specification over 1999–2012 for US firms, excluding any US MNEs that ever established a JV or a WFOE in China before 2012. 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.

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

where f denotes firms and j 4-digit SIC industries. The dependent variable Δy_{fj} is the DHS growth rate of firm-level outcomes, $100 \times \frac{y_{fj,12} - y_{fj,99}}{0.5(y_{fj,12} + y_{fj,99})}$ (Davis et al., 1998). We include NTRgap_j to control for sectoral reductions in US-China trade-policy uncertainty post-WTO (Pierce and Schott, 2016).[12] $\mathbf{X}_{fj}$ is a vector of additional controls. ε_{fj} is the error term. Regressions are weighted by firms' initial sales. Standard errors are clustered at the SIC 3-digit level.

ΔJV_j 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, normalized by total industry j sales in 1998[13]:

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

where $\mathcal{J}_{j,t}$ is the set of JV affiliates in industry j in year t. In the numerator, we use domestic sales rather than total sales because these JV affiliates could have engaged in processing trade, serving export markets without engaging in complex manufacturing activity. We include JV affiliates from MNEs of all source countries in the numerator because negative competition effects may arise not only from US MNEs but also from other countries' MNEs.

We include the sectoral WFOE exposure, defined analogously to the JV exposure, to compare how JVs and WFOEs differ in their effects on US firms:

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

[12] NTRgap_j is the potential increase in US tariffs on Chinese goods had Congress failed to renew China's Normal Trade Relations status annually prior to the granting of Permanent Normal Trade Relations.

[13] This is a standard industry-level FDI exposure measure in the literature (e.g., Aitken and Harrison, 1999).

Table 1: JV and Negative Outcomes for US Firms (OLS)

Dep. var.	ΔSale		ΔEmp.		ΔCapital		ΔExport	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
ΔJV_j	−14.27***	−17.42***	−15.51***	−18.86***	−11.76***	−15.72***	−14.96***	−26.72***
	(2.62)	(2.09)	(3.33)	(2.38)	(3.24)	(2.86)	(5.23)	(3.06)
$\Delta WFOE_j$	9.07	2.41	17.83**	2.95	7.30	−3.65	16.50	4.01
	(6.04)	(4.20)	(8.19)	(3.63)	(8.94)	(5.45)	(14.36)	(5.50)
$NTRgap_j$	−2.06**	−2.22***	−2.12**	−2.27***	−2.15***	−2.24***	−2.87*	−2.97***
	(0.79)	(0.57)	(0.91)	(0.61)	(0.80)	(0.54)	(1.49)	(0.87)
Controls		✓		✓		✓		✓
Mean dep. var.	7.84	7.84	−11.27	−11.27	9.75	9.75	27.79	27.79
# clusters	105	105	105	105	105	105	99	99
N	949	949	949	949	949	949	767	767

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). ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). In columns 1–2, 3–4, 5–6, and 7–8, the outcomes are DHS growth of US firms' sales, employment, capital, and exports (1999–2012). The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. The even columns add US sectoral employment and value-added growth (1993–1998), US import penetration (1996), US production-worker shares (1993), US computer and high-tech investment shares (1990), China's sectoral value-added growth (1995–1997), China's changes in the subsidy-to-gross-output ratio and the Herfindahl index of subsidies, and 1-digit industry dummies. All regressions are weighted by initial sales.

Table 1 reports the results. Column 1 reports the estimate for sales growth, which is negative and significant at the 1% level. A 1 percentage point increase in industry j's JV exposure is associated with 0.14 percentage point lower sales growth for US firms in that industry over the same period. In column 2, we add industry-level controls for technological trends, pretrends, and Chinese subsidy intensity.[14] Were these factors driving our results, the estimate would attenuate once we add these controls. Instead, it remains negative and significant. JV exposure is also negatively correlated with growth in employment, capital, and exports (cols. 3–8). It is likewise negatively correlated with the outcomes of firms in other countries (excluding China and the US), further supporting the view that JV investment in

[14]The technological-trend controls, following Acemoglu et al. (2016), are 1996 US import penetration, 1993 production-worker shares, 1990 computer and high-tech investment shares, and 1-digit industry dummies. The pretrend controls are US sectoral employment and value-added growth (1993–1998) from the NBER manufacturing database and China's sectoral value-added growth (1995–1997) from China's National Bureau of Statistics. Consistent with this, US and China's pretrends are uncorrelated with JV exposure (Table B8). The subsidy control is changes in share of total subsidies to gross output and the Herfindahl index of subsidy distribution (1999–2012), following Aghion et al. (2015). Years of these controls vary with data availability.

China intensified global competition (Table B7).

In contrast to the consistently negative and significant JV estimates, the WFOE coefficients show no consistent pattern and are imprecisely estimated for most of the outcomes. This difference is consistent with WFOEs having no local Chinese partner to absorb technology, and supports the view that the negative effects could originate mainly from technology transfer to local partners rather than from foreign investment in China per se.

To partially address endogeneity, we consider an IV strategy as a robustness check. The IV is industry-level changes in FDI by Korean and Japanese MNEs into India. From the India side, this lets us extract the push factors behind Korean and Japanese outward FDI, plausibly exogenous to China's sectoral productivity growth and to policies targeting particular Chinese sectors. They are relevant because the JV and WFOE exposures include affiliates of MNEs from all countries, including Korea and Japan. Appendix B.1 discusses the IV strategy and its identifying assumptions in detail. The IV estimates are similar in magnitude to the OLS estimates. The results also remain robust to including firms that formed JVs, clustering at the 4-digit industry level, restricting the sample to 1999–2007 (pre-Great Recession), and using employment-based weights (Table B9).

Within-Industry Evidence. We provide further evidence using variation in product overlap across firms within industries. For the sample of US firms that have never engaged in either a JV or a WFOE (so no MNEs in the sample), we estimate the following event-study regression:

$$y_{fjt} = \sum_{\tau=-5}^{7} \beta_\tau \left(\text{TNIC}_{fk} \times D^{\text{JV}}_{j\tau t}\right) + \sum_{\tau=-5}^{7} \gamma_\tau \left(\text{TNIC}_{fk'} \times D^{\text{WFOE}}_{j\tau t}\right)$$
$$+ \sum_{\tau=-5}^{7} D^{\text{JV}}_{j\tau t} \left(\text{TNIC}_{fk} \times \mathbf{X}_{k,-1}\right)' \boldsymbol{\alpha}_\tau + \sum_{\tau=-5}^{7} D^{\text{WFOE}}_{j\tau t} \left(\text{TNIC}_{fk'} \times \mathbf{X}_{k',-1}\right)' \boldsymbol{\varrho}_\tau + \delta_f + \delta_{jt} + \varepsilon_{fjt}, \quad (3.6)$$

where j SIC 4-digit denotes industries. Log sales is the baseline firm outcome. $D^{\text{JV}}_{j\tau t} = \mathbb{1}[t - t^{\text{JV}}_j = \tau]$ are event-time dummies that equal 1 when year t is τ years from sector j's first-JV event year (t^{JV}_j). $D^{\text{WFOE}}_{j\tau t}$ is defined analogously for WFOE. We include industry-year fixed effects δ_{jt} to absorb time-varying industry-level shocks, and firm fixed effects δ_f. Standard errors are clustered at the SIC 3-digit level.

Here k and k' are the first US publicly listed firms to form, respectively, a new additional

JV and WFOE in f's sector over 1999–2012, and their formation years define the event years. Because the sample contains only never-participating firms and δ_{jt} absorbs each sector's event timing, β_τ and γ_τ are identified from within-industry-year variation in exposure rather than from comparisons of earlier- to later-treated firms, avoiding the staggered difference-in-differences problem. Over 1999–2012, 87 industries had a first-JV or -WFOE event (38 a first JV, 79 a first WFOE, and 30 both). We restrict observations to the event-time window -5 to 7 for both event types, and the estimation sample consists of 2,330 firms.

TNIC_{fk} is the standardized pre-event average of the text-based network industry classification (TNIC) similarity between firms f and k (Hoberg and Phillips, 2016). TNIC is a time-varying pairwise measure of product-market similarity, obtained as the cosine similarity of word-frequency vectors from the business descriptions in firms' annual 10-K filings.[15] Interacting pre-event TNIC_{fk} with the first-JV (or -WFOE) indicators generates firm-specific exposure. Firms with higher TNIC_{fk} are more likely to be adversely affected by the first JV, because greater product overlap exposes them to more intense competition once it forms.

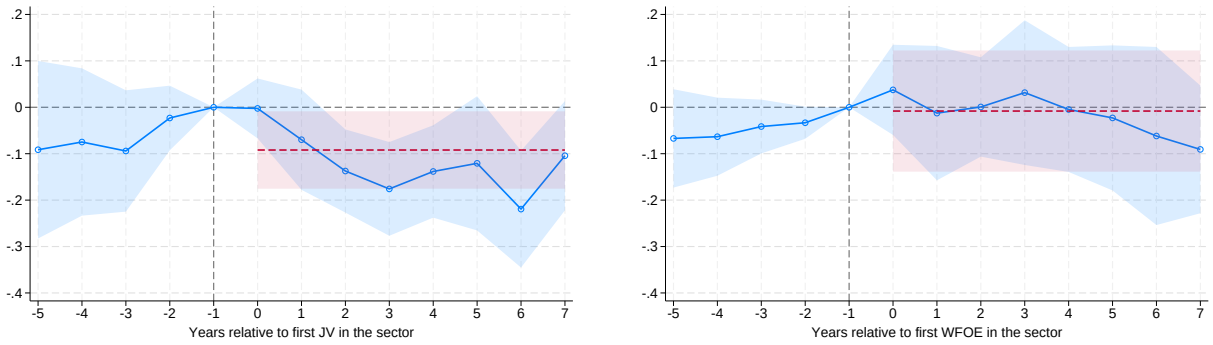
The decision to form a JV or WFOE may itself reflect selection on positive shocks, so the first-JV or first-WFOE events could capture the mechanical effects of those shocks rather than effects specific to the JV or WFOE. For example, an MNE's productivity gains can reduce other US firms' size through US domestic competition, independently of the JV or WFOE channel. We mitigate this concern by including the pre-event (at $\tau = -1$) levels and growth rates of the first-JV and first-WFOE MNEs' sales and TFPR in $\mathbf{X}_{k,-1}$ and $\mathbf{X}_{k',-1}$, each interacted with the corresponding TNIC exposure and event dummies.[16]

Figure 2 reports the results. Only after the first-JV event do sales of firms with greater product overlap gradually decline more. The estimates imply that a one-standard-deviation-higher TNIC_{fk} is associated with a 10% larger decline in sales on average. Consistent with the across-sector evidence, we find declines after the first-JV event but not after the first-WFOE event, again supporting the view that a JV intensifies future global competition more than a WFOE, as it operates through a local Chinese partner and is therefore more likely to transfer

[15] Hoberg and Phillips (2016) show that the Compustat historical business-segment data rarely reclassify firms and effectively hold a firm's product portfolio fixed over time, whereas TNIC provides a time-varying, firm-specific, continuous pairwise measure.

[16] TFPR is obtained from İmrohoroğlu and Tüzel (2014). Due to potential measurement errors in TFPR growth, we use the average of two consecutive growth rates.

Figure 2: Within-Sector Event Study. JVs, Product Overlap, and US Firm Sales



A. Log sales, JV B. Log sales, WFOE

Notes. This figure reports the event-study estimates of equation (3.6). 95% confidence intervals, based on standard errors clustered at the SIC 3-digit level, are shown. β_{-1} and γ_{-1} are normalized to zero. Panels A and B report the coefficients associated with the first-JV and first-WFOE events over 1999–2012. The red lines represent the average pooled diff-in-diff coefficients, with their 95% confidence intervals.

technology to a Chinese firm. This difference and the absence of pre-trends also suggest that our results are unlikely to be driven by the mechanical effect of the MNEs' expansion.

The results are robust to excluding the interaction terms with $\mathbf{X}_{k,-1}$ and $\mathbf{X}_{k',-1}$, to replacing continuous exposure with a 75th-percentile dummy, and to using employment and capital as alternative outcomes. They are also not driven by sectoral composition and hold when we restrict to sectors that experienced both JV and WFOE events. Figure B3 reports these checks.

Taking Stock. Together, the two facts reinforce the view that JV investment in China strengthened Chinese firms through technology diffusion and, as their growth intensified global competition, harmed other US firms that did not form JVs themselves. We acknowledge clear limitations in our empirical analyses. The choice of whether and with whom to form a JV is not exogenous, and unobserved shocks may also drive the negative US outcomes we document. While the difference in magnitude between the JV and WFOE estimates and the stability of our estimates to additional controls provide suggestive evidence that these alternative explanations are unlikely to drive our results, we cannot completely rule them out. We therefore do not interpret our findings as causal. Instead, we build a model consistent with these two facts to perform counterfactuals, and we use these reduced-form correlations as targeted moments for calibration or non-targeted moments to validate the model.

4. Simple Model of Joint Venture and Business Stealing

==- In this section we develop a simple model of joint venture formation that highlights a business stealing channel. All proofs are collected in Appendix C.

Setup. The economy has two countries, the US and China, indexed by $c \in \{H, F\}$, and a fixed set of three firms, a US leader, a US fringe, and a Chinese firm, indexed by $i \in \{h, \tilde{h}, f\}$. Firms compete under monopolistic competition, each producing a unique variety that is tradable subject to an iceberg cost $\tau > 1$.

Labor is the only factor of production, used to make the varieties or a freely tradable outside good whose price is normalized to 1. The production function of the outside good is linear in labor with unit productivity in both countries, so free trade pins down the wage at 1 in both countries.

Each country is populated by L_c representative households who each supply one unit of labor inelastically, are immobile across countries, and own the domestic firms. We normalize $L_H = 1$.

Household. Households have quasi-linear preferences $U_c = C_c^0 + \ln C_c$, where C_c^0 is consumption of the outside good and C_c is a CES composite of varieties,

$$C_c = \left[\sum_{i \in \{h, \tilde{h}, f\}} \psi_i^{\frac{1}{\sigma}} c_{ci}^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}}, \quad \psi_h = \psi_f = 1, \quad \psi_{\tilde{h}} > 0,$$

with $\sigma > 1$ the elasticity of substitution and $\psi_i > 0$ demand shifters, normalized to one for the US leader and the Chinese firm. The budget constraint is $C_c^0 + P_c C_c = 1 + \frac{\Pi_c}{L_c}$, where P_c is the price index and Π_c is the total profit of country c's firms.

Firms and JV. Each firm's production function is linear in labor, $y_i = z_i l_i$. Delivered unit costs are w/z_i at home and $\tau w/z_i$ abroad, and firms charge the constant markup $\frac{\sigma}{\sigma-1}$ over unit cost. With quasi-linear utility, total differentiated expenditure in market c equals L_c, so firm i's operating profit there is $\pi_{ci} = \frac{1}{\sigma} s_{ci} L_c$, where s_{ci} is firm i's sales share in market c. Firm i's total operating profit is $\Pi_i = \sum_c \pi_{ci}$.

Under a JV, the US leader shares its technology with the Chinese rival, but in return it produces inside China and avoids the trade cost. The two firms form the JV through Nash bargaining over a transfer T that maximizes the Nash product $(\Delta\Pi_h + T)^{\xi} (\Delta\Pi_f - T)^{1-\xi}$ subject to $\Delta\Pi_h + T \geq 0$ and $\Delta\Pi_f - T \geq 0$, where $\Delta\Pi_i$ is firm i's change in operating profit from the JV and ξ is the leader's bargaining power. The net payoffs are $\Delta\Pi_h + T$ for the leader and $\Delta\Pi_f - T$ for the Chinese firm. For tractability, we give the US leader zero bargaining power, $\xi = 0$.

The fringe firm cannot form a JV and is best interpreted as a non-participant in JVs rather than as a small firm. The economically relevant distinction is JV participation, and the firms harmed by business stealing need not be small. Indeed, Fact 2 documents declines among publicly listed US firms, which are typically large.

The US leader and the fringe firm are at the frontier, $z_h = z_{\tilde{h}} = 1$. The Chinese firm starts behind and catches up to the frontier only when a JV transfers the leader's technology,

$$z_f = \begin{cases} 1/b & \text{without a JV} \\ 1 & \text{with a JV} \end{cases}, \qquad b > 1. \tag{4.1}$$

Total operating profit in each market is fixed at $\sum_i \pi_{ci} = \frac{L_c}{\sigma}$, regardless of firm productivity. A JV therefore leaves total producer profit unchanged, $\sum_i \Delta\Pi_i = 0$, and only reshuffles it across firms while lowering price indices.

Equilibrium. In equilibrium, households maximize utility, firms maximize profits, and markets clear. The JV always forms and the US fringe loses profit (Proposition 1). With zero leader bargaining power, the leader is held to its outside option, so $\Delta\Pi_h + T = 0$, and the Chinese firm retains the entire surplus.[17]

Proposition 1 (Business stealing)**.** *The US leader's and the Chinese firm's combined operating-profit gain equals the US fringe's loss and is strictly positive,*

$$\Delta\Pi_h + \Delta\Pi_f = -\Delta\Pi_{\tilde{h}} > 0,$$

[17]The transfer can take either sign. When the gap b is large, the Chinese firm gains and compensates the leader for the business it loses to the stronger rival, so $T > 0$. When b is close to 1, the leader's operating profit instead rises through cheaper access to China, so it pays into the deal and $T < 0$.

so the JV is always jointly profitable and forms in equilibrium. With zero leader bargaining power the transfer is $T = -\Delta\Pi_h$, and the Chinese firm retains the entire surplus $\Delta\Pi_h + \Delta\Pi_f$.

Welfare. The welfare change after JV formation decomposes into a consumer surplus gain and a fringe profit loss,

$$\Delta W_H = \underbrace{-\ln \frac{P_H^{\text{JV}}}{P_H}}_{\text{Consumer surplus gain} > 0} + \underbrace{\Delta\Pi_{\tilde{h}}}_{\text{Fringe profit loss} < 0}. \tag{4.2}$$

The consumer surplus gain is always positive, because the Chinese firm's productivity improvement lowers the US price level, while the fringe's profit always falls. The sign of the welfare effect depends on which force dominates. In the US, the consumer gain partly offsets the fringe's loss. The fringe's loss in the Chinese market, however, brings no offsetting gain to US consumers, so a larger Chinese market L_F makes the business stealing effect larger and a net welfare loss more likely. When China's market size L_F is sufficiently large, the JV can lower US welfare (Proposition 2).

Proposition 2 (Welfare and foreign market size)**.** *(i) ΔW_H is strictly decreasing in the foreign market size, L_F, $\partial \Delta W_H / \partial L_F < 0$. (ii) Let $\bar{L}_F \equiv \dfrac{\tau^{2(1-\sigma)}(1 - b^{1-\sigma})}{(\sigma - 1)(2 - \tau^{1-\sigma} - b^{1-\sigma})}$. The JV can lower US welfare, $\Delta W_H \leq 0$, when $L_F \geq \bar{L}_F$, and always raises it, $\Delta W_H > 0$, when $L_F < \bar{L}_F$.*

A higher fringe demand shifter $\psi_{\tilde{h}}$ amplifies the business stealing effect, because the part of total sector profit that the leader does not internalize becomes larger. A larger technology gap b means a bigger catch-up jump, which lowers the US price more, raising the consumer surplus gain, but also reduces the fringe's profit more, amplifying the business stealing effect. When the fringe's profit is sufficiently large, the second force dominates and a larger gap reduces US welfare.

Proposition 3 (Comparative statics)**.** *Suppose $L_F > \dfrac{\tau^{2(1-\sigma)}}{\sigma - 1}$.*[18] *Then the following hold.*
(i) (Demand shifter) There exists a threshold $\bar{\psi}_{\tilde{h}}$ such that the JV raises US welfare, $\Delta W_H > 0$, if $\psi_{\tilde{h}} \in [0, \bar{\psi}_{\tilde{h}})$, and lowers it, $\Delta W_H \leq 0$, if $\psi_{\tilde{h}} \in [\bar{\psi}_{\tilde{h}}, \infty)$.
(ii) (Technology gap) There exists a threshold $\hat{\psi}_{\tilde{h}}$ such that a larger gap b lowers the US welfare effect of the JV, $\partial \Delta W_H / \partial b < 0$, for $\psi_{\tilde{h}} > \hat{\psi}_{\tilde{h}}$.

[18] This bound exceeds $\bar{L}_F$, so the assumption implies $L_F > \bar{L}_F$ in Proposition 2 and the JV can lower US welfare.

Taking Stock. The simple model highlights our business stealing effect, whereby the leader does not internalize the profit loss of non-JV participants, an externality that can reduce US welfare. Although the simple model captures this channel, it abstracts from several important forces, such as uncertainty in technology leakage, general equilibrium effects, and endogenous productivity dynamics driven by innovation and diffusion, which are central to understanding China's catch-up. We embed these forces in our quantitative framework, described in the next section.

5. Quantitative Framework

In this section, we develop a two-country growth model with oligopolistic competition, innovation, and joint ventures, to quantitatively explore this channel.

5.1 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 $\tau^x \geq 1$ 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.

5.2 Household

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

$$U_{Ht} = \int_t^\infty \exp\big(-\rho(s-t)\big) \ln C_{Hs} ds\,, \quad \text{s.t.} \quad r_{Ht} A_{Ht} + w_{Ht} L_H = P_{Ht} C_{Ht} + T_{Ht} + \dot{A}_{Ht}\,, \quad (5.1)$$

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}) with the expenditure share of the tradable sector β: $C_{Ht} = (C^T_{Ht})^\beta (C^N_{Ht})^{1-\beta}$. Its price index is $P_{Ht} = \left(\frac{P^T_{Ht}}{\beta}\right)^\beta \left(\frac{P^N_{Ht}}{1-\beta}\right)^{1-\beta}$, where P^T_{Ht} and P^N_{Ht} denote the price indices of tradable and non-tradable sector output, respectively.

5.3 Sectors

Tradable sector output aggregates varieties produced by Home and Foreign firms across products:

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

where y_{ijt} and y^*_{ijt} are the quantities of varieties produced by domestic and foreign firms, and the superscript "$*$" indicates exported varieties. ψ_i is firm i's demand shifter. Leaders in both countries and the JV share a common value $\psi = \psi_h = \psi_f = \psi_v$, while fringe firms share a different common value $\tilde{\psi} = \psi_{\tilde{h}} = \psi_{\tilde{f}}$, normalized so that $\psi + \tilde{\psi} = 1$. Varieties are imperfectly substitutable within products, with elasticity of substitution $\sigma \in (1, \infty)$. To keep the new variety created by a JV from mechanically raising utility, we neutralize the love of variety by normalizing the product-level aggregator with the sum of demand shifters $\sum_{i\in\mathcal{I}_{jt}} \psi_i$, where $\mathcal{I}_{jt} = \mathcal{I}_H \cup \mathcal{I}_{Fjt}$ is the set of firms supplying product j (Benassy, 1996). In the quantitative

section we also report results that preserve love of variety. The 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.

In the non-tradable sector, a perfectly competitive representative firm produces the sectoral good with a linear technology, $Y_{Ht}^N = Z_{Ht}^N L_{Ht}^N$, where Z_{Ht}^N is exogenous productivity that grows at rate g^N. With perfect competition, $P_{Ht}^N = \frac{w_{Ht}}{Z_{Ht}^N}$.

5.4 Firms

Production and Market Structure. A firm produces a variety 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: $\mathcal{Y}_{ijt} = y_{ijt} + \tau y_{ijt}^*$.

Within each product, the two leaders (Home and Foreign) and the JV (if established) engage in Bertrand competition, charging variable markups over their marginal cost. 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

$$p_{hjt} = \frac{1 - \frac{\sigma-1}{\sigma} s_{hjt}}{\frac{\sigma-1}{\sigma}(1 - s_{hjt})} \frac{w_{Ht}}{z_{hjt}} \qquad \text{and} \qquad p_{hjt}^* = \frac{1 - \frac{\sigma-1}{\sigma} s_{hjt}^*}{\frac{\sigma-1}{\sigma}(1 - s_{hjt}^*)} \frac{\tau(1+t_{Ft}) w_{Ht}}{z_{hjt}}, \tag{5.2}$$

where s_{hjt} and s_{hjt}^* are its sales shares in Home and Foreign. Its operating profits in the two markets are

$$\pi_{hjt} = \frac{s_{hjt}}{\sigma - (\sigma-1)s_{hjt}} P_{Ht}^T C_{Ht}^T \qquad \text{and} \qquad \pi_{hjt}^* = \frac{s_{hjt}^*}{\sigma - (\sigma-1)s_{hjt}^*} P_{Ft}^T C_{Ft}^T, \tag{5.3}$$

and its total operating profit is $\Pi_{hjt} = \pi_{hjt} + \pi_{hjt}^*$.

Fringe firms, unlike the others, charge the constant monopolistic-competition markup $\frac{\sigma}{\sigma-1}$, so their prices are $p_{\tilde{h}jt} = \frac{\sigma}{\sigma-1}\frac{w_{Ht}}{z_{\tilde{h}jt}}$ and $p_{\tilde{h}jt}^* = \frac{\sigma}{\sigma-1}\frac{\tau(1+t_{Ft})w_{Ht}}{z_{\tilde{h}jt}}$, with operating profits $\pi_{\tilde{h}jt} = \frac{1}{\sigma} s_{\tilde{h}jt} P_{Ht}^T C_{Ht}^T$ and $\pi_{\tilde{h}jt}^* = \frac{1}{\sigma} s_{\tilde{h}jt}^* P_{Ft}^T C_{Ft}^T$. They can be interpreted as a continuum of atomistic,

homogeneous firms with total mass 1.

Innovation. Leaders in both countries can improve productivity through successive innovations. They choose the Poisson arrival rate of innovation, x_{ijt}, subject to the convex cost function

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

where h^r_{ijt} is the R&D labor employed by firm i, α_{cr} scales the innovation cost in country c, and γ governs its curvature. Upon a successful innovation, which arrives at rate x_{ijt}, productivity jumps to $z_{ij,t+\Delta t} = \lambda \times z_{ijt}$, where $\lambda > 1$ is the step size.

Fringe firms do not innovate. Their productivity improves only through technology diffusion from the domestic leader within the same product.

Joint Venture. A Home leader may partner with the Foreign leader in the same product to establish a JV in Foreign, which produces a new variety using Foreign labor. The JV serves the Foreign market without trade costs but pays them when exporting back to Home. A Home leader's incentive to form a JV rises with Foreign market size, the wage differential, and trade costs, capturing the proximity-concentration trade-off (Helpman et al., 2004).[19]

The JV does not innovate. Its productivity tracks the Home leader's, $z_{vjt} = z_{hjt}/\tau^z$, where $\tau^z > 1$ is the productivity loss from multinational production. This loss reflects the barriers to operating in a foreign regulatory environment and added communication costs (Holmes et al., 2015). Sharing the headquarters' productivity reflects the nonrivalry of ideas.[20]

We assume that JVs maximize their own profits rather than the joint profit with their parent firms.[21] The Home leader receives fraction κ of the JV's total profit Π_{vjt}, and the Foreign leader retains $1 - \kappa$. This fraction is fixed across JVs and taken as given by firms. Richer contractual arrangements may affect welfare and JV formation, but we adopt this

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

[20] 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. Bilir and Morales (2020) document productivity spillovers from MNE-headquarters R&D to foreign affiliates.

[21] This can be micro-founded through an agency problem in which the JV manager maximizes only the JV's profit, not the joint profit with its parents.

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.[22] Second, a constant split lets us focus on the business stealing effect on US fringe firms.

A Home leader chooses the Poisson arrival rate d_{hjt} of a JV opportunity, which requires h^d_{hjt} workers:[23]

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

When an opportunity arrives, the Home and Foreign leaders engage in Nash bargaining over a one-time fee C_{jt} paid by the Home leader (or received, if negative), which we detail in the next subsection. The fee ensures mutual gains for the two leaders, with the surplus split according to their bargaining power.[24] Once established, a JV operates until it exits exogenously at rate χ.

Technology Diffusion. There are three types of technology diffusion. The first is direct diffusion through JVs, between the two partners. While the JV operates, the lagging partner, either the Home or the Foreign leader, learns from its more advanced partner and catches up to that partner's productivity with Poisson intensity ϕ, consistent with Fact 1.[25]

The second and third, domestic and international diffusion, are standard in the literature. Fringe firms catch up to the domestic leader's productivity with Poisson intensity δ^D (domestic diffusion).[26] JVs also indirectly benefit Foreign fringe firms through this domestic diffusion. Finally, with Poisson intensity δ^F, the lagging leader within product j catches up to the advanced leader's productivity (international diffusion). The intensity δ^F captures

[22] 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.

[23] h^d_{hjt} represents expenses for training local managers or legal processing costs of setting up a new firm. We impose the same curvature as in innovation. In principle we could allow two different curvature parameters, but calibrating the JV cost curvature would require information on the cost of setting up a JV, which is rarely available in the data.

[24] This one-time fee generalizes the fixed or sunk costs typically assumed in the FDI literature. The size of the cost and the party that bears it are determined endogenously through the Nash bargaining between Home and Foreign leaders, based on the technology gap. Because Home leaders form JVs only when the added profit exceeds the fee, and because formation is probabilistic, our model captures the extensive margin of JVs observed in the data.

[25] Immediate catch-up means firms further behind gain more from diffusion, the advantage of backwardness (Gerschenkron, 1962), documented at the micro level by Choi and Shim (2024).

[26] Lucas and Moll (2014); Perla and Tonetti (2014); König et al. (2022) assume similar domestic diffusion.

diffusion across countries through channels other than JVs.[27]

5.5 Equilibrium

State Variable. The vector of technology gaps between leaders and fringe firms, $\mathbf{m}_{jt} = \{m^F_{jt}, m^{DH}_{jt}, m^{DF}_{jt}\}$, is the payoff-relevant state variable. Conditional on JV status and other aggregates, $\mathbf{m}_{jt}$ determines each firm's profit within product j. These gaps are

$$\frac{z_{hjt}}{z_{fjt}} = \lambda^{m^F_{jt}}, \qquad \frac{z_{hjt}}{z_{\tilde{h}jt}} = \lambda^{m^{DH}_{jt}}, \qquad \frac{z_{fjt}}{z_{\tilde{f}jt}} = \lambda^{m^{DF}_{jt}}. \tag{5.4}$$

$m^F_{jt} \in \{-\bar{m}, \ldots, 0, \ldots, \bar{m}\}$ is the cross-country gap between the two leaders, positive when the Home leader leads. m^{DH}_{jt}, m^{DF}_{jt} are the within-country gaps between each leader and its fringe, similarly bounded by $\bar{m}$. These bounds are large and exogenous, which keeps the state space finite and computation feasible. The JV's productivity is tied to the Home leader's, so we need not track it separately. Because products are symmetric, we drop the product subscript j from $\mathbf{m}_{jt}$ and from firm-level variables.

Value Function. Let $V_{ht}(\mathbf{m}; \mathcal{J})$ denote the value of the Home leader h in a product, given the state $\mathbf{m}$ and JV status $\mathcal{J} \in \{0, 1\}$. We present the value functions only for the case where the Home leader leads, $m^F > 0$, and relegate the remaining cases to Appendix D.

Without a JV, the Home leader's value function is

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m}; 0) - \dot{V}_{ht}(\mathbf{m}; 0) = \max_{x_{ht}, d_{ht}} \Bigg\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^\gamma}{\gamma} w_{Ht} - \alpha_{Hd} \frac{(d_{ht})^\gamma}{\gamma} w_{Ht} \\ & + x_{ht} \Big(V_{ht}(\mathbf{m} + (1,1,0); 0) - V_{ht}(\mathbf{m}; 0) \Big) + x_{ft} \Big(V_{ht}(\mathbf{m} + (-1,0,1); 0) - V_{ht}(\mathbf{m}; 0) \Big) \\ & + d_{ht} \Big(V_{ht}(\mathbf{m}; 1) - V_{ht}(\mathbf{m}; 0) - C_t(\mathbf{m}) \Big) + \sum_{\mathbf{m}'} \mathbb{T}(\mathbf{m}'; \mathbf{m}) \Big(V_{ht}(\mathbf{m}'; 0) - V_{ht}(\mathbf{m}; 0) \Big) \Bigg\}, \end{aligned} \tag{5.5}$$

[27] See, for example, Buera and Oberfield (2020) and de Souza et al. (2025) on international trade, Rachapalli (2021) on supply chains, and Santacreu (2025) and Choi and Shim (forthcoming) on formal licensing.

where $\mathbb{T}(\mathbf{m}';\mathbf{m})$ gives the diffusion transition rates from $\mathbf{m}$ to $\mathbf{m}'$,

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

The first line of the right-hand side is flow profit, operating profit net of innovation and JV-formation costs. The second line is the value change from the Home leader's own innovation and from the Foreign leader's innovation. On the third line, the first term is the value change from forming a JV, and the second is the value change from exogenous diffusion within the product.

With a JV in place, the value function is

$$\begin{aligned} r_{Ht} V_{ht}(\mathbf{m};1) - \dot{V}_{ht}(\mathbf{m};1) = \max_{x_{ht}} \Bigg\{ & \Pi_{ht}(\mathbf{m}) - \alpha_{Hr} \frac{(x_{ht})^\gamma}{\gamma} w_{Ht} + \kappa \Pi_{vt}(\mathbf{m}) \\ & + x_{ht}\Big(V_{ht}(\mathbf{m} + (1,1,0);1) - V_{ht}(\mathbf{m};1)\Big) + x_{ft}\Big(V_{ht}(\mathbf{m} + (-1,0,1);1) - V_{ht}(\mathbf{m};1)\Big) \\ & + \phi\Big(V_{ht}(0, m^{DH}, m^F + m^{DF};1) - V_{ht}(\mathbf{m};1)\Big) + \chi\Big(V_{ht}(\mathbf{m};0) - V_{ht}(\mathbf{m};1)\Big) \\ & + \sum_{\mathbf{m}'} \mathbb{T}(\mathbf{m}';\mathbf{m})\Big(V_{ht}(\mathbf{m}';1) - V_{ht}(\mathbf{m};1)\Big) \Bigg\}. \end{aligned} \tag{5.6}$$

Now the flow profit includes the Home leader's share of the JV's profit, $\kappa\Pi_{vt}(\mathbf{m})$, and the Home leader no longer forms a new JV, so $d_{ht} = 0$. On the third line, the first term is the direct JV diffusion, through which the Foreign leader catches up to the Home leader at rate ϕ, and the second term is the value change from the JV's exogenous exit at rate χ.

Optimal Innovation and Joint Venture Rates. The optimal innovation rate is

$$x_{ht}(\mathbf{m};\mathcal{J}) = \left(\frac{V_{ht}(\mathbf{m} + (1,1,0);\mathcal{J}) - V_{ht}(\mathbf{m};\mathcal{J})}{\alpha_{Hr} w_{Ht}}\right)^{\frac{1}{\gamma-1}}, \qquad \mathcal{J} \in \{0,1\}, \tag{5.7}$$

and the optimal JV rate is

$$d_{ht}(\mathbf{m}) = \max\left(\left(\frac{V_{ht}(\mathbf{m};1) - V_{ht}(\mathbf{m};0) - C_t(\mathbf{m})}{\alpha_{Hd} w_{Ht}}\right)^{\frac{1}{\gamma-1}}, 0\right). \tag{5.8}$$

Bargaining and Joint Venture Fees. Conditional on a JV opportunity, the Home and Foreign leaders set the fee $C_t(\mathbf{m})$ paid by the Home leader through Nash bargaining,

$$C_t(\mathbf{m}) \underset{C}{\operatorname{argmax}} \left\{\left(\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C\right)^{\xi}\left(\Delta^{\text{JV}} V_{ft}(\mathbf{m}) + C\right)^{1-\xi}\right\} = (1-\xi)\Delta^{\text{JV}} V_{ht}(\mathbf{m}) - \xi \Delta^{\text{JV}} V_{ft}(\mathbf{m})$$
$$\text{s.t.} \quad \Delta^{\text{JV}} V_{ht}(\mathbf{m}) - C \geq 0, \qquad \Delta^{\text{JV}} V_{ft}(\mathbf{m}) + C \geq 0 \tag{5.9}$$

where ξ is the Home leader's bargaining power. $\Delta^{\text{JV}} V_{it}(\mathbf{m}) = V_{it}(\mathbf{m};1) - V_{it}(\mathbf{m};0)$ is the value change for firm $i \in \{h, f\}$ from forming a JV. Note that $d_{ht}(\mathbf{m}) > 0$ when $\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{ft}(\mathbf{m}) > 0$; otherwise, $d_{ht}(\mathbf{m}) = 0$.

When the Foreign leader lags ($m^F > 0$), it gains substantially from direct diffusion and is willing to pay for the JV, so the Home leader tends to receive a fee, $C_t(\mathbf{m}) \leq 0$. When $m^F \leq 0$, the Foreign leader does not gain from direct diffusion, but the Home leader still benefits from the JV profit, so the Home leader pays a fee, $C_t(\mathbf{m}) > 0$.

When the Home leader forms a JV, it anticipates lower future profits as Foreign firms become more productive through direct and indirect diffusion from the JV. It internalizes these dynamic losses and is compensated for them through the bargaining fee. It does not, however, internalize the profit losses the JV inflicts on Home fringe firms. As a result, there may be over-investment in JVs relative to the US optimum, as shown in the simple model. Symmetrically, the Foreign leader does not internalize the diffusion benefit to Foreign fringe firms, which may imply under-investment from China's perspective.

Combining Equations (5.8) and (5.9), the optimal JV rate is

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

The rate increases with the total surplus $\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{ft}(\mathbf{m})$, for given ξ. This surplus rises with the technology gap, because both the JV's profit and the Foreign leader's diffusion

gains increase with the gap.

Market Clearing. Asset markets clear, $A_{Ht} = \int_0^1 \sum_{i \in \mathcal{I}_H} V_{ijt} \, \mathrm{d}j$, where the right-hand side is the total value of Home firms. Goods markets clear,

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

Labor markets clear,

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

The balance of payments holds,

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

Similar asset, goods, and labor market clearing conditions hold in Foreign.

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

Definition 1. *A Markov perfect equilibrium consists of sequences of prices* $\{r_{ct}, w_{ct}, p_{ijt}, p^*_{ijt}, P^T_{ct}, P^N_{ct}, P_{ct}\}$ *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 in Definition 1 in which* $\{C_{ct}, A_{ct}\}$ *grow at a constant rate* g*, and* r_{ct} *and* $\mu_t(\mathbf{m}; \mathcal{J})$ *stay constant over time.*

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

$$\int_t^\infty \exp\big(-\rho(s-t)\big) \ln\big((1+\omega)C_{Hs}^b\big)\,\mathrm{d}s = U_{Ht}^c\,, \tag{5.10}$$

where C_{Hs}^b is baseline consumption at s and U_{Ht}^c is the present discounted utility under the counterfactual.

5.6 Taking Stock

A novel feature of our model is the business stealing effect of Home leaders' JVs and technology transfer on Home fringe firms. Technology diffusion through JVs makes Foreign firms more competitive globally, which lowers Home firms' profits. When making JV decisions, Home leaders internalize their own future profit losses from this rising competition but not the losses they impose on the Home fringe. As in the simple model, the diffusion rate ϕ and the leader demand shifter ψ govern how much Home leaders over-invest in JVs relative to the Home optimum. A higher ϕ intensifies future competition for Home fringe firms. A higher ψ gives leaders larger market shares, so they internalize more of total industry profit and align their JV decisions more closely with the Home optimum. It is important that Home fringe firms do produce in equilibrium for Home leaders' JV decisions to deviate meaningfully from the social optimum for the Home country.

6. 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 $N(b, \mathcal{V})$, with mean b and variance $\mathcal{V}$. A positive b means that, on average, US leaders start with higher productivity than Chinese leaders. Lacking precise information on the magnitude of domestic diffusion δ^D, we set $\delta^D = \delta^F = \delta$ and

Table 2: Calibration Summary

Parameter	Value	Description	Source / Main target
Panel A. Directly from data			
L_F/L_H	2.83	Labor supply of China / US	Human-capital adj. pop. (Lee and Lee, 2016)
β	0.40	Tradable consumption share	1997 US BEA IO table
χ	0.08	JV exit rate	Avg. exit rate in CN (Chen et al., 2023)
$\mathcal{V}$	0.7	Variance of initial gap	Variance of productivity ratio in 1999
κ, ξ	0.54	US JV profit share	Avg. equity share of MNE
g^N	0.017	Non-tradable prod. growth rate	US GDP per capita growth rate (2011–2019)
t_t^H, t_t^F		US/CN import tariff rates	Avg. import tariff rates
τ^z		JV iceberg technology cost	
Panel B. 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	2.85	Iceberg trade cost	Bai et al. (2024)
Panel C. Internally calibrated by SMM			
α_{Hr}	0.67	US R&D cost scale	Avg. R&D / sales of US firms
α_{Fr}	0.89	CN R&D cost scale	Long-run avg. gap= 0
α_{Hd}	2.17	US JV scale	Avg. JV sales shares
λ	1.12	Step size	US GDP growth rate
b	19.7	Avg. technology gap	1999 mfg. value-added / emp. CN/US ratio
δ	0.029	Domestic & Intl. diffusion	2020 mfg. value added / emp. CN/US ratio
ψ	0.25	Leader & JV demand shifter	Mfg. US Compustat firm sales / gross output
ϕ	0.159	Direct diffusion	Direct effect on Chinese parents, Fig. 1

check robustness to alternative values.

We calibrate 23 parameters in three steps. We take 11 directly from the data, calibrate 4 externally from the literature, and estimate 8 jointly by simulated method of moments (SMM). For each guess of the 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 11 parameters $\{L_H, L_F, \beta, \chi, \kappa, \xi, g^N, \mathcal{V}, t_t^H, t_t^F, \tau^z\}$ 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 BEA 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.

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.[28] 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 JV iceberg cost τ^z captures the JV's productivity loss. We compute the TFPQ ($= \frac{\text{Sale}^{\sigma/(\sigma-1)}}{\text{Emp}}$) of US MNEs and of their affiliates and take the ratio. The ratio is 1.7, so we set $\tau^z = 1.7$, which implies that JV productivity is about 40% lower than that of the US leaders.

The 4 parameters $\{\rho, \sigma, \gamma, \tau\}$ are externally calibrated from the literature. We set the discount rate to $\rho = 0.03$. We set the elasticity of substitution to $\sigma = 4$ following Broda and Weinstein (2006). We set $\gamma = 2$, the curvature of the innovation cost function, following Acemoglu et al. (2018). The iceberg trade cost between the US and China is set to $\tau = 2.85$ following Bai et al. (2024).

The 8 parameters $\mathbf{\Theta} = \{\alpha_{Hr}, \alpha_{Fr}, \alpha_{Hd}, \lambda, b, \phi, \psi, \delta\}$ are jointly estimated by minimizing the distance between model moments $M_m(\mathbf{\Theta})$ and their data counterparts M_m^D:

$$\min_{\mathbf{\Theta}} \sum_{m=1}^{8} \left(\frac{M_m^D - M_m(\mathbf{\Theta})}{\frac{1}{2}(M_m^D + M_m(\mathbf{\Theta}))} \right)^2.$$

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.[29] 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

[28] 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. It lies between 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.

[29] This calibration yields $\alpha_{Fr} > \alpha_{Hr}$ because China has a larger labor endowment. If $\alpha_{Hr} = \alpha_{Fr}$, average Chinese productivity on the balanced growth path would exceed US productivity.

average GDP growth rate over 2011–2019.

The initial gap b 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. This moment is informative, as a higher δ^F implies faster Chinese convergence.

We calibrate the leaders' demand shifter ψ to match the share of US Compustat 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, which have the scale and resources to form joint ventures abroad. Publicly listed firms indeed account for the bulk of US outbound FDI to China in our Orbis data (72% of JV-affiliate sales and 82% of WFOE-affiliate sales by US firms in 1999).[30]

We calibrate the direct diffusion parameter ϕ from Fact 1 by running a pooled diff-in-diff regression analogous to equation (3.1) on model-generated data and matching the average of the post-event coefficients. 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 each match consists of a leader and a fringe firm in the same industry. The estimated β equals 0.2 in our data, which we target in our calibration.[31]

Table 2 summarizes the estimation results. The model moments closely match their data counterparts (Panel A of Table 3). We obtain $b = 19.7$, implying that US firms are initially 9 times as productive as Chinese firms on average. We obtain $\phi = 0.159$ and $\delta^F = \delta^D = 0.029$, implying that forming a JV raises the diffusion intensity between leaders from 2.9% to 18.8%.

The model also matches three non-targeted moments (Panel B of Table 3). First, and most importantly, it reproduces the negative outcomes for US firms (Fact 2). When we estimate equation (3.3) using model-generated data, we obtain a coefficient of -17.72, close to its empirical counterpart of -14.27. Second, it predicts a positive relationship between the initial US-China technology gap and sectoral JV exposure, which we also see in the data. Larger gaps make JVs more attractive because they raise the total JV surplus through higher

[30] Because the fringe is calibrated to non-Compustat firms, the model does not capture business-stealing effects among Compustat firms themselves, which our within-sector evidence in Fact 2 documents. Our welfare losses are therefore a lower bound, as a larger fringe demand shifter amplifies the negative welfare effect, as the simple model predicts. The comparative statics based on the full quantitative model in the next section also confirms this.

[31] To replicate the regression in the model, we simulate 100,000 products whose technology gap between the US and China is randomly drawn from the calibrated initial distribution. Since innovation and diffusion are stochastic, products become heterogeneous in their technology gaps over time.

Table 3: Targeted and Non-Targeted Moments in the Model and the Data

Moment	Model	Data
Panel A. Targeted Moments		
Direct effect on CN partners (Panel A, Figure 1)	0.197	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	0.107	0.110
Mfg. value added per emp. ratio (CN / US), 1999	0.083	0.084
Mfg. value added per emp. ratio (CN / US), 2020	0.386	0.382
Leader firms' sales share	0.281	0.280
Long-run avg. productivity ratio	1.000	1.000
Panel B. Non-Targeted Moments		
US negative outcome (col. 1, Table 1)	−17.72	−14.27
Sectoral regression, JV exposure & initial gap	0.110	0.169
JV fee / JV sales ratio (%) (Branstetter et al., 2006)	1.17	1.50

JV profits and larger gains from diffusion. 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 that advantage over time and reducing the gains from trade (Samuelson, 2004). Finally, the average ratio of JV fee flow to JV sales flow is 1.17%, which falls within the range reported by Branstetter et al. (2006) from US BEA microdata.[32]

7. Quantitative Exercises

7.1 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

[32]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. 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 it has the largest sales, operating with the US leader's productivity, lower Chinese wages, and no iceberg trade costs on Chinese sales.

Table 4: Baseline vs. Counterfactual Scenarios: Welfare Effects (%)

JV ban	in 1999	in 1999 coordinated JV	in 2025
US	1.07	−0.88	−0.83
China	−8.78	−1.60	−2.44

Notes. This table reports consumption-equivalent welfare changes for the US and China under three counterfactuals. The first bans new JVs from 1999 onward, the second does so under coordinated JV decisions in both the baseline and counterfactual, and the third bans new JVs from 2025 onward. Welfare is computed relative to the baseline with no ban, where positive values indicate that the ban raises welfare. Welfare in columns 1 and 2 is measured from 1999 onward, and in column 3 from 2025 onward.

an unanticipated shock to all agents in 1999.

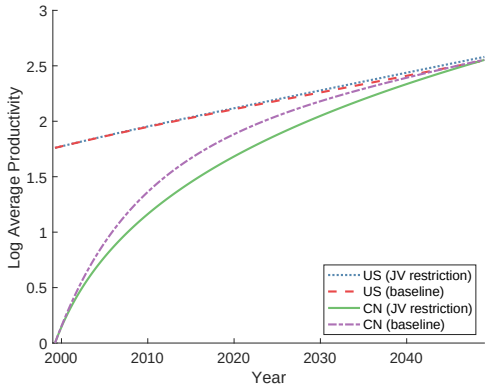
Table 4 reports the consumption-equivalent welfare effects. The JV ban in 1999 raises US welfare by 1.1% but reduces China's welfare by 8.8%. In the counterfactual, the US-China technology gap widens and China's convergence slows (Panels A and B of Figure 3). Without JV-driven technology diffusion, Chinese leaders' productivity grows more slowly.[33] The US innovation rates increase after the JV ban, which will be discussed in details below (Panel C, counterfactual minus baseline). 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 reveals richer consumption dynamics. The lines plot counterfactual consumption divided by baseline consumption for each country. US consumption falls immediately after the JV ban 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 ban 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.

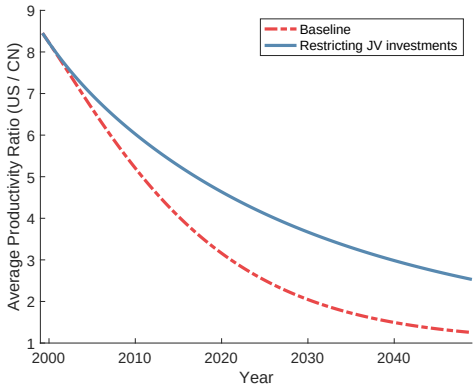
Three forces shape US innovation rates under the JV ban. The option-value and market-size effects push innovation higher when JVs are available, but the leakage effect works in the opposite direction. The *option-value effect* is the incentive to innovate before forming a JV. By

[33] 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.

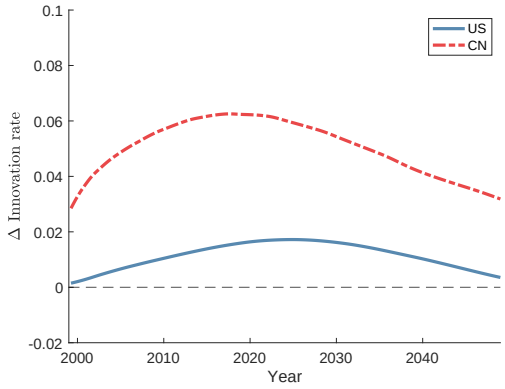
Figure 3: Effects of Banning Joint Venture Investments in 1999: Dynamics of Productivity, Innovation, and Consumption



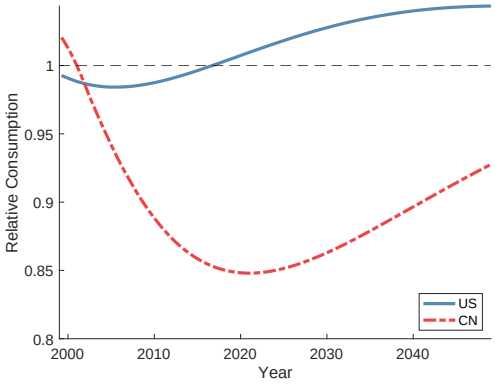
A. Log leader productivity



B. Productivity ratio (US/China)



C. Innovation rate (counterfactual − baseline)



D. Consumption (counterfactual / baseline)

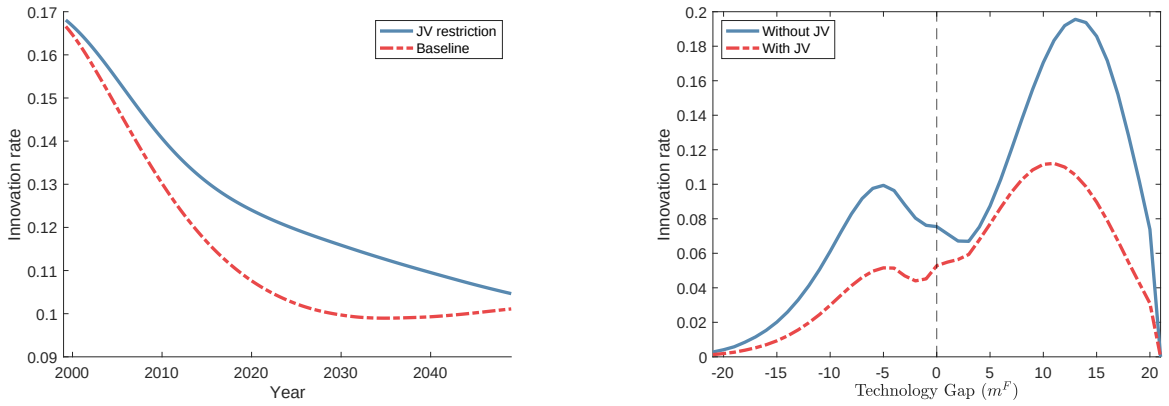
Notes. This figure compares dynamics under the counterfactual (JV ban in 1999) to the baseline. Panel A plots average log leader productivity for the US and China. Panel B plots the US–China productivity ratio. Panel C plots the difference in average innovation rates (counterfactual minus baseline) for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

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, potentially depressing innovation.

The *leakage effect* works the other way. JVs accelerate technology diffusion to Chinese rivals, eroding future profits and dampening returns to innovation (Helpman, 1993).[34] Any extra

[34]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.

Figure 4: 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 $m^{DF} = m^{DH} = \bar{m}$.

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, and products with JVs exhibit lower innovation intensities than those without, conditional on technology gaps (Panel B of Figure 4).[35] In our calibration, as JVs are established in more products, the overall mix shifts toward products with lower innovation rates.[36] 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.[37]

Next, we decompose the welfare effect of banning JVs by income source (Table 5). Real

[35]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 technology gap toward zero, where innovation rates fall below the two peaks.

[36]In 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.

[37]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).

Table 5: Baseline vs. Ban of Joint Venture Investments in 1999

	Baseline	Ban on JV	Changes (%)
US leader profit (own + JV + JV fee)	0.047	0.039	−17.08
Own profit	0.035	0.038	10.04
JV profit	0.008	0.000	n/a
JV fee revenue	0.004	0.000	n/a
US fringe profit	0.066	0.070	6.33
US labor income	0.888	0.906	2.11
US total real income	1.000	1.015	1.49

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.

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 demand, wages, and prices, arises from leaders' 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 and show that when leaders internalize fringe profits, fewer JVs are established and the real wage decreases following a JV ban.

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

We interpret the direct diffusion parameter ϕ as the model counterpart of the quid-pro-quo policy. It is the extra rate of US-to-China diffusion triggered by JV formation, beyond domestic and international diffusion, so setting $\phi = 0$ isolates the mandated technology-

transfer component of the policy. Relative to the baseline with $\phi = 0.159$, eliminating it raises US welfare by 3.1% and lowers Chinese welfare by 3.8%. These results match Holmes et al. (2015), who find that the quid-pro-quo policy benefits China at the expense of the US. Our China magnitude (3.8%) is close to their 4.69%, but our US gain (3.1%) is far larger than their 0.45%, because our model adds strategic competition and innovation decisions that are absent from theirs.

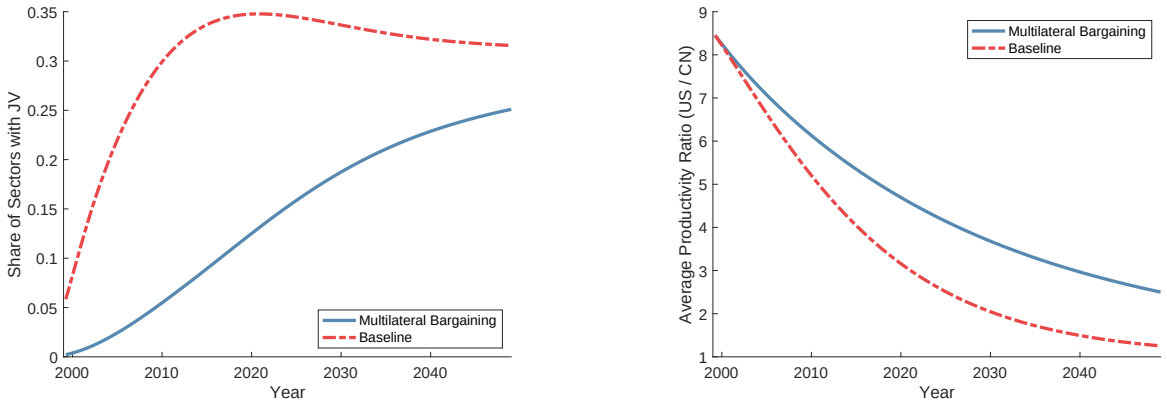
To further examine the mechanisms and the robustness of these results, we consider alternative modeling assumptions (Table D3). When we shut down the innovation channel by setting the R&D cost parameter to infinity, the JV ban still raises US welfare by 0.37%, though the magnitude is 65% smaller (0.37% vs. 1.07%). 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 banning JVs become smaller from this love-of-variety loss, but they remain positive at 0.65%. Finally, we consider constant markups as in standard monopolistic competition, and the results remain robust. Overall, the US welfare gains from banning JVs are robust to these alternative modeling assumptions. Sensitivity checks with respect to key parameters (ϕ, δ^F, δ^D, b, and κ) also confirm robustness (Table D4).

7.2 Business Stealing as the Key Market Failure

We showed that over-investment in JVs lowers US welfare relative to the JV-ban counterfactual. To further illustrate how the business stealing effect leads to such over-investment, we consider coordinated JV decisions, under which a JV can be established only if US leaders compensate fringe firms for their future losses (i.e., leaders internalize fringe profits). Specifically, we add a bargaining problem between US leaders and fringe firms, in addition to the one between US and Chinese leaders (see Appendix D.1 for details). As a result, a JV is established only when the total surplus to the US leader and fringe firms (gross of transfers) 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.[38]

[38]The modified bargaining outcomes are $C = (1-\xi)\{\Delta^{\text{JV}} V_{ht}(\mathbf{m}) + \Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m})\} - \xi \Delta^{\text{JV}} V_{ft}(\mathbf{m})$ and $C^E = -\Delta^{\text{JV}} V_{\tilde{h}t}(\mathbf{m})$, where C^E is the fee paid by US leaders to fringe firms.

Figure 5: 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

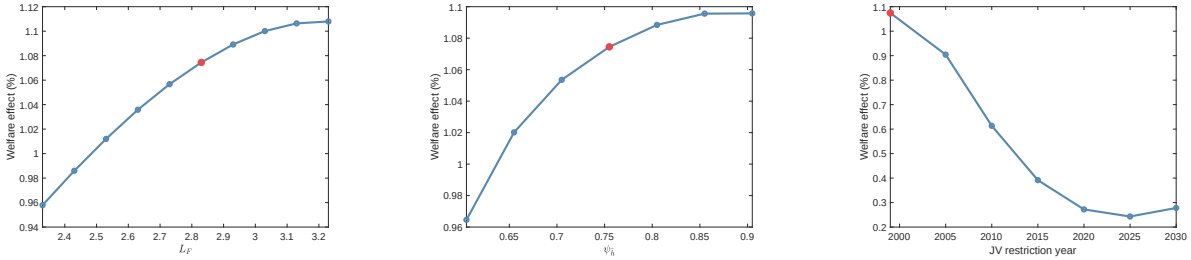
Coordinated JV decisions raise US welfare by 2.0% relative to the uncoordinated baseline. By requiring leaders to compensate their own fringe firms, coordination makes JVs more costly and better aligns leaders' interests with the social optimum. As Panel A of Figure 5 shows, fewer JVs are formed under coordination. With fewer JVs, technology diffusion to China slows and China's convergence rate declines (Panel B).

Coordination therefore alters the welfare impact of a JV ban. A JV ban from 1999 onward decreases US welfare by 0.9% (col. 2 of Table 4) and Chinese welfare by 1.6%. Because coordination already make US leaders' interests closer to 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.

Decomposing US welfare by income source as in Table 5, we find that under coordination, leader profit and importantly the real wage fall when JVs are banned (Table D2). This confirms that the large general-equilibrium effect under the uncoordinated baseline was itself a consequence of leader firms failing to internalize fringe profits. When this failure is corrected via coordination, the real wage channel reverses sign.

Furthermore, Propositions 2(i) and 3(i) suggest that the welfare effect of banning JVs increases with foreign market size L_F and the fringe demand shifter $\psi_{\tilde{h}}$, because larger values of each amplify the business stealing effect. Figure 6 shows that this pattern also holds in the full quantitative model, where the welfare effect is larger when either L_F or $\psi_{\tilde{h}}$ is larger.

Figure 6: Comparative Statics over Foreign Market Size, Fringe Demand Shifter, and Technology Gap (Timing). Welfare Effects of JV Ban (%)



A. Foreign Market Size L_F B. Fringe Demand Shifter $\psi_{\tilde{h}}$ C. Technology gap b (timing)

Notes. This figure reports consumption-equivalent welfare changes of the US from banning JV investments over different values of L_F, $\psi_{\tilde{h}}$, and timing of JV bans. The red dots denote for baselien calibrated values in Panels A and B, and the baseline ban timing in Panel C.

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

Next, in light of recent policy debates, we consider banning 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 0.8% (col. 3 of Table 4, measured in 2025). By 2025, the US-China technology gap has narrowed substantially (Figure D2), so technology diffusion and the resulting business stealing effect on US fringe firms have weakened. Although the ban still slightly widens the US-China technology 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 technology gap narrows (Panel C of Figure 6), implying that the timing of the ban determines its welfare consequences. This result is also consistent with Proposition 3(ii) from the simple model, which states that the welfare effect is increasing in the technology gap, as a larger gap amplifies the business stealing effect.

8. Conclusion

The intensifying economic and geopolitical rivalry between the US and China has spurred ongoing debates over whether US firms transfer too much technology to China and whether 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 business stealing effects on other US firms. 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, banning joint ventures in industries with particularly large US-China technology gaps, or coordinating policy 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 banning 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 opens several avenues for future research. On the empirical side, our novel findings 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 diffusion. 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, 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. Another compelling avenue for future research is to explore the interaction between optimal tariffs and joint venture policies. 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. We see this as a promising direction 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, private firms, and JV and WFOE affiliates 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 with 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 Table B7, 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 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 a 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.

Concordance between SIC and CIC. We construct the concordance between the 4-digit 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 exposure 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.

B. Appendix: Empirics

B.1 Fact 2: 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 an IV strategy 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 strategy, detailed below, exploits 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):

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

where the FDI exposure is defined analogously to the JV and WFOE exposures:

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

We construct the IV as the ratio of the total sales of FDI in India affiliated with MNEs

from Japan or South Korea, relative to China's total sector sales in 1998:

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

$\mathcal{J}_{jt}^{\text{IN,JP-KR}}$ 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, 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.

There can be two main potential threats to identification, namely, 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.

We investigate these concerns by inspecting pretrends and industry-level balance, fol-

lowing Borusyak et al. (2022) (Table B1). 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. We also find no significant correlation with the pre-1999 5-year growth of US firm-level outcomes.

We assess industry-level balance by checking the correlation between our IV and initial industry characteristics that could be related to unobserved shocks. The export platform is unlikely to be a significant concern, as there are no significant correlations between bilateral import penetration (import-to-domestic absorption ratio) and the IV for China, India, and the US. Moreover, sectors with a higher IV 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, the absence of correlations with these variables supports the plausibility of the exclusion restriction.

Three variables related to technological change are significantly correlated with the IV, overall US import penetration (excluding China, India, Japan, and 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 omitted variable bias due to these unobservables is unlikely to be a major concern.

Table B2 reports the results. The IV estimates are qualitatively similar to the OLS estimates. The IV is strong. The results remain robust to the additional controls.

Table B1: Pretrend and Shock Balance Test of the IV

Balance variable	$IV_j^{JP,KR}$			
	Coef.	SE	p-val.	N
Panel A. Industry-level Pretrend				
Δ Log gross output 1993–1998	0.11	(0.06)	[0.06]	383
Δ Log emp. 1993–1998	0.10	(0.06)	[0.10]	383
Δ Log PPI 1993–1998	0.05	(0.05)	[0.35]	383
Δ US import (ex. CN, IN, JP, KR) / absorption 1996-1998	0.04	(0.02)	[0.12]	383
Δ US-CN import / absorption 1996-1998	−0.05	(0.06)	[0.41]	383
Panel B. Industry-level balance				
US-CN import / absorption 1996	−0.06	(0.04)	[0.14]	383
US-IN import / absorption 1996	−0.02	(0.01)	[0.24]	383
CN-IN import / absorption 1996	−0.01	(0.04)	[0.77]	383
IN-CN import / absorption 1996	−0.02	(0.02)	[0.13]	383
JV sales share 1998	−0.04	(0.04)	[0.28]	383
Number of JV firms to total number of firms ratio 1998	0.02	(0.01)	[0.12]	383
US share (ussh) 1996	−0.06	(0.05)	[0.26]	383
US import (ex. CN, IN, JP, KR) / absorption 1996	0.14	(0.04)	[0.00]	383
Ratio of capital to wage-bills 1993	0.01	(0.07)	[0.91]	383
Ratio of wage bills to value-added 1993	0.03	(0.05)	[0.56]	383
R&D intensity 1993	0.08	(0.11)	[0.47]	383
Production workers' share of employment 1993	0.27	(0.06)	[0.00]	383
High-tech investment shares 1990	−0.13	(0.09)	[0.15]	383
Computer investment shares 1990	−0.18	(0.05)	[0.00]	383
Panel C. Firm-level Pretrend				
Δ Sale 1993–1998	−2.51	(17.45)	[0.89]	723
Δ Emp. 1993–1998	−0.68	(23.08)	[0.98]	723
Δ Capital 1993–1998	18.31	(12.88)	[0.16]	723
Δ Export 1993–1998	−19.20	(35.88)	[0.59]	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 OLS estimates from regressing each balance variable on the IV based on South Korea and Japan's FDI in India. In Panels A and B, each observation is a 4-digit SIC industry, all variables are standardized, and regressions are weighted by initial gross output. R&D intensity is the 1993 sectoral mean of R&D-to-sales ratios, calculated from Compustat. High-tech and computer investment shares are obtained from Acemoglu et al. (2016), varying at the SIC 3-digit level. In Panel C, each observation is a US firm, the dependent variables are DHS growth of sales, employment, capital, and exports over 1993–1998, and regressions include the NTR gap control and are weighted by initial sales.

Table B2: Negative Outcomes for US Firms (IV)

Dep. var.	ΔSale		ΔEmp		ΔCapital		ΔExport	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Second stage								
ΔFDI_j	−15.33***	−18.21***	−16.79***	−18.42***	−10.59***	−12.80***	−13.29**	−27.00***
	(3.59)	(3.89)	(4.26)	(4.08)	(3.28)	(3.63)	(5.96)	(5.83)
NTRgap_j	−1.91*	−2.15***	−1.88	−2.14***	−1.89**	−2.05***	−2.45	−2.79***
	(0.97)	(0.64)	(1.20)	(0.71)	(0.93)	(0.61)	(1.74)	(1.02)
AR	18.75	19.46	18.57	18.16	10.69	11.52	5.18	18.72
AR p-val.	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.02]	[0.00]
Mean dep. var.	7.84	7.84	−11.27	−11.27	9.75	9.75	27.79	27.79
Panel B. First stage								
IV	12.97***	12.27***	12.97***	12.27***	12.97***	12.27***	12.80***	12.02***
	(1.23)	(1.09)	(1.23)	(1.09)	(1.23)	(1.09)	(1.29)	(1.10)
NTRgap_j	−0.01	−0.02*	−0.01	−0.02*	−0.01	−0.02*	−0.01	−0.02*
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
First-stage F	112.03	126.78	112.03	126.78	112.03	126.78	98.60	120.40
Add. ctrl.		✓		✓		✓		✓
# clusters	105	105	105	105	105	105	99	99
N	949	949	949	949	949	949	767	767

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 IV estimates of equation (B.1) for US firms. ΔFDI_j is defined in equation (B.2) and is instrumented by the IV based on South Korea and Japan's FDI in India. In columns 1–2, 3–4, 5–6, and 7–8, the dependent variables are the DHS growth rates of sales, employment, capital, and exports over 1999–2012. Panel A reports the second-stage estimates, and Panel B the first stage, where the dependent variable is the endogenous regressor ΔFDI_j. 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 as in Table 1. AR and AR p-val. are the Anderson-Rubin statistic and its p-value. First-stage F is the Kleibergen-Paap F-statistic. All regressions are weighted by initial sales.

B.2 Additional Figures and Tables

Table B3: 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	16.24	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

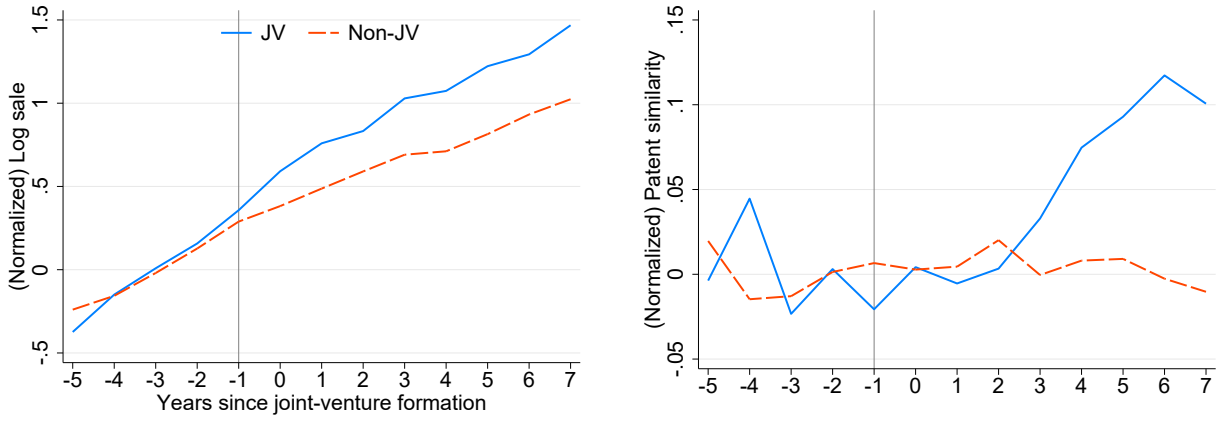
Notes. This table presents descriptive statistics for treated and control firms from five to one years before the event. Column 9 reports t-statistics for the mean differences between treated and control groups, while Column 10 provides the corresponding p-values (in brackets), computed using standard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

Table B4: 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, and the inverse hyperbolic sine transformation and dummies of exports, cumulative patent stock, and yearly new patents.

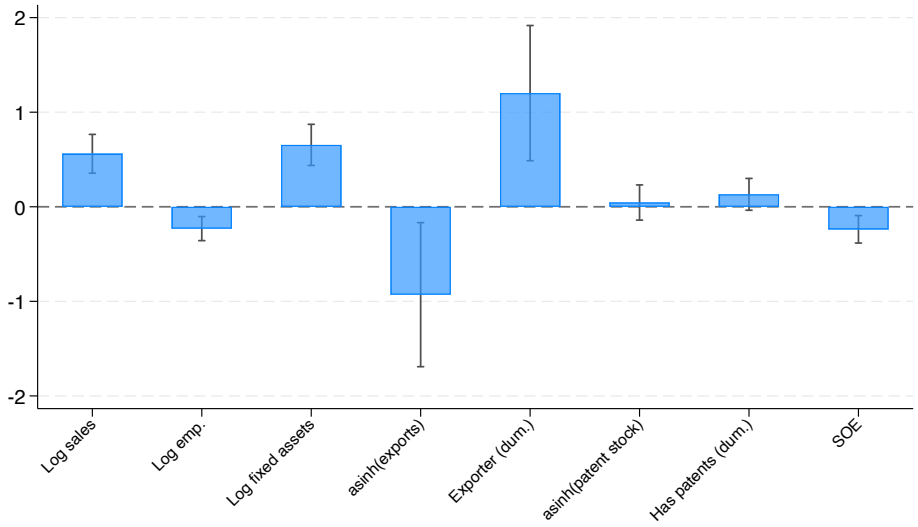
Figure B1: Raw Plots. Direct Effects of Joint Venture Formation on Chinese Partner Firms



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: Propensity Score Matching. Logit Estimation Result



Notes. The figure plots the estimated coefficients from the logit regression used to construct the propensity score for matching. 95% confidence intervals, with standard errors clustered at the two-digit industry level, are reported. The dependent variable equals one for firms that form a joint venture and zero for candidate control firms, and all covariates are measured in the year before the joint venture. Every covariate is standardized to mean zero and unit standard deviation, so each bar measures the change in the log-odds of forming a JV associated with a one-standard-deviation increase in that covariate and is comparable across covariates. The covariates are log sales, log employment, log fixed assets, the inverse hyperbolic sine (asinh) of exports, an indicator for being an exporter, the asinh of the cumulative patent stock (depreciated at 30% per year), an indicator for holding any patents, and an indicator for state-owned enterprises (SOE).

Table B5: 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	7,457	7,457	1,746	7,457	7,457	7,457	7,457	7,457

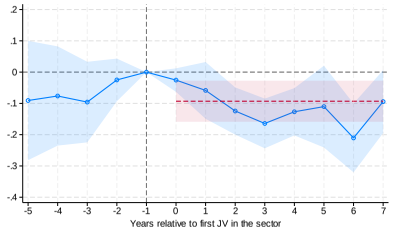
Notes. Standard errors, shown in parentheses, are clustered at the match and firm levels. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. This table reports the estimated event-study coefficients of equation (3.1). β_{-1} is normalized to zero. The dependent variables are log sales (col. 1), the inverse 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 B6: Robustness. Alternative Number of Matches and Depreciation Rates for Patent Stock. Direct Effects of Joint Venture Formation on Chinese Partner Firms

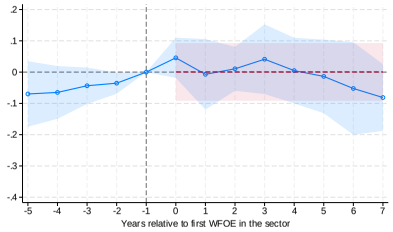
Robustness	Alt. number of matches						Alt. dep. rate		
	2	3	5	2	3	5	0	0.2	0.5
Dep. var.	Log sales			Technological proximity					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
5 years before	−0.16	−0.17	−0.09	0.05	−0.04	−0.02	0.03	0.03	0.02
	(0.13)	(0.11)	(0.10)	(0.06)	(0.08)	(0.09)	(0.05)	(0.06)	(0.06)
4 years 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 year 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 years 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 years 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 years 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 years 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 years 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 years 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.

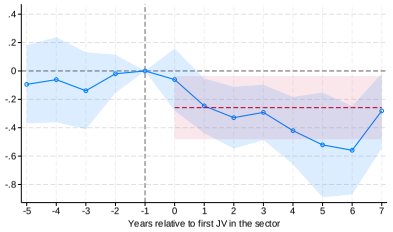
Figure B3: Robustness: No Controls, Alternative Exposure Measure, and Alternative Outcomes. Within-Sector Event Study. JV and Negative Outcomes for US Firms



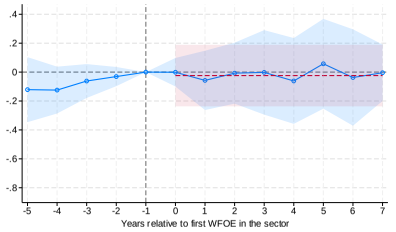
A. Sales, no ctrl, JV



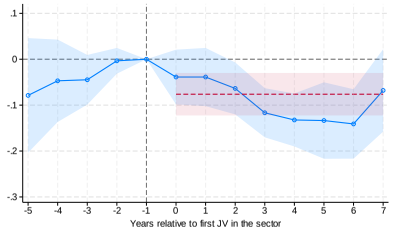
B. Sales, no ctrl, WFOE



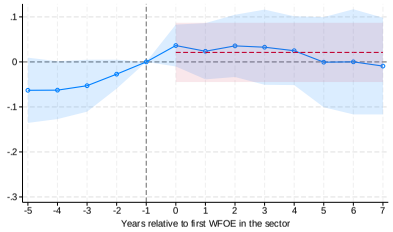
C. Sales, p75, JV



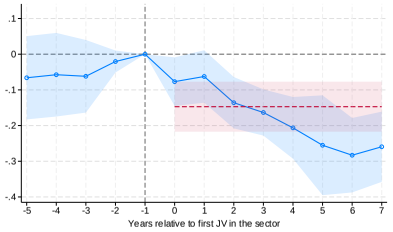
D. Sales, p75, WFOE



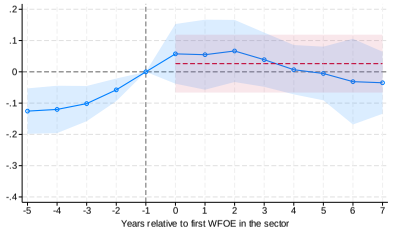
E. Emp., JV



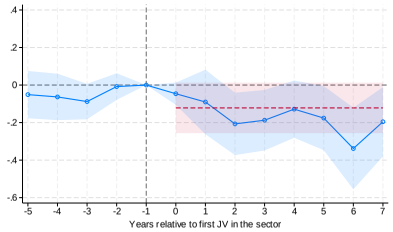
F. Emp., WFOE



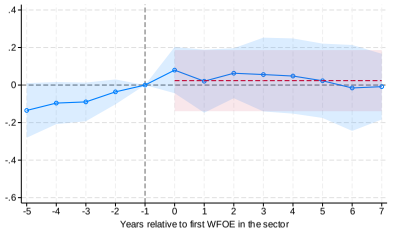
G. Capital, JV



H. Capital, WFOE



I. Sales. both events, JV



J. Sales, both events, WFOE

Notes. This figure illustrates the event study estimation results of equation (3.6). 95% confidence intervals, based on standard errors clustered at the SIC 3-digit level, are reported. β_{-1} and γ_{-1} are normalized to zero. Each panel reports coefficients for the first-JV or first-WFOE event over 1999–2012. The dependent variable is log sales in Panels A through D and I through J, log employment in Panels E and F, and log capital in Panels G and H. Panels A and B use no controls, and Panels C and D use the alternative p75 exposure measure. In Panels I and J, the sample is restricted to industries that experience both JV and WFOE events. In all panels except A and B, the participants' controls are included.

Table B7: Negative Outcomes for Global Firms (OLS)

Dep. var.	ΔSale		ΔEmp		ΔCapital	
	(1)	(2)	(3)	(4)	(5)	(6)
ΔJV_j	−5.24**	−4.18**	−0.62	−2.09	−3.54*	−4.07**
	(2.35)	(2.01)	(1.45)	(1.87)	(2.07)	(1.78)
$\Delta WFOE_j$	7.12	7.82	9.72*	12.16**	5.10	8.93
	(5.53)	(7.07)	(5.35)	(4.88)	(6.31)	(6.10)
$NTRgap_j$	−1.12*	−1.10***	−0.50	−0.48*	−0.84**	−0.82***
	(0.59)	(0.35)	(0.33)	(0.29)	(0.41)	(0.29)
Controls		✓		✓		✓
Mean dep. var.	−1.36	−1.36	7.22	7.22	−9.48	−9.48
# clusters	117	117	117	117	117	117
N	1,416	1,416	1,416	1,416	1,416	1,416

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). In columns 1–2, 3–4, and 5–6, the dependent variables are DHS growth rates of sales, employment, and capital over 1999–2012. The NTR gap is the tariff increase on Chinese goods from a failed NTR renewal. The even columns include additional controls as in Table 1. All regressions are weighted by initial employment.

Table B8: Pretrends Cannot Explain 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	−0.01	−0.01	−0.00	−0.00
	(0.01)	(0.01)	(0.01)	(0.01)
$\Delta WFOE_j$		0.05		0.00
		(0.04)		(0.05)
$NTRgap_j$		0.00		0.00
		(0.00)		(0.00)
Mean dep. var.	0.24	0.24	0.31	0.31
# 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. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5). In Panel A, the dependent variables in columns 1–2 and 3–4 are DHS growth of China's sectoral gross output and value-added (1995–1997). In Panel B, the dependent variables in columns 1–2, 3–4, and 5–6 are DHS growth of US firms' sales, employment, and capital (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 initial sales in Panel B.

Table B9: Robustness. Negative Outcomes for US Firms (OLS)

Robustness	Alt. sample full-sample	Alt. clustering 4-digit level	Alt. sample period 1999–2007	Alt. weight emp.
	(1)	(2)	(3)	(4)
ΔJV_j	-14.00^{***}	-14.27^{***}	-15.55^{***}	-11.25^{***}
	(2.34)	(2.64)	(4.71)	(2.78)
$\Delta WFOE_j$	8.51	9.07	12.40^{**}	1.16
	(7.77)	(5.91)	(5.70)	(6.71)
$NTRgap_j$	-1.80^{**}	-2.06^{**}	-1.20^{**}	-0.89
	(0.79)	(0.79)	(0.53)	(0.74)
Mean dep. var.	8.69	7.84	16.46	6.03
# clusters	105	173	110	105
N	1,017	949	1,368	949

Notes. Standard errors 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. The dependent variable is the DHS growth rate of sales. ΔJV_j and $\Delta WFOE_j$ are defined in equations (3.4) and (3.5) and exclude each firm's own JV and WFOE affiliates. Each column reports one robustness check. Column 1 uses the full sample, including US firms that formed a JV or WFOE in China. Column 2 clusters standard errors at the SIC 4-digit level. Column 3 restricts the sample period to 1999–2007 and computes both JV and WFOE exposures over 1999–2007. Column 4 weights by initial employment. Unless noted otherwise, standard errors are clustered at the SIC 3-digit level and regressions are weighted by initial sales. All columns include the NTR gap control.

C. Proofs of the Simple Model

Throughout we use the CES aggregates $P_c^{1-\sigma} = \sum_i \psi_i p_{ci}^{1-\sigma}$, which take the explicit forms

$$P_H^{1-\sigma} = 1 + \psi_{\tilde{h}} + \tau^{1-\sigma} b^{1-\sigma}, \qquad (P_H^{\text{JV}})^{1-\sigma} = 1 + \psi_{\tilde{h}} + \tau^{1-\sigma},$$
$$P_F^{1-\sigma} = \tau^{1-\sigma}(1 + \psi_{\tilde{h}}) + b^{1-\sigma}, \qquad (P_F^{\text{JV}})^{1-\sigma} = 2 + \psi_{\tilde{h}} \tau^{1-\sigma},$$

where the superscript JV denotes for post-JV variables. Recall $\tau^{1-\sigma} \in (0,1)$ and $b^{1-\sigma} \in (0,1]$, since $\tau > 1$, $b \geq 1$, and $\sigma > 1$.

Proof of Proposition 1. Because every firm charges the common markup $\frac{\sigma}{\sigma-1}$, total operating profit in each market is $\sum_i \pi_{ci} = \frac{1}{\sigma} L_c \sum_i s_{ci} = \frac{L_c}{\sigma}$, independent of costs. The JV leaves this total unchanged, so summing over $c \in \{H, F\}$, $\Delta\Pi_h + \Delta\Pi_f + \Delta\Pi_{\tilde{h}} = 0$. The JV raises both cost aggregates,

$$(P_H^{\text{JV}})^{1-\sigma} - P_H^{1-\sigma} = \tau^{1-\sigma}(1 - b^{1-\sigma}) \geq 0, \qquad (P_F^{\text{JV}})^{1-\sigma} - P_F^{1-\sigma} = (1 - \tau^{1-\sigma}) + (1 - b^{1-\sigma}) > 0.$$

The fringe's own delivered costs are unchanged, so $\Pi_{\tilde{h}}$ decreases due to decrease in the price indices:

$$\Delta\Pi_{\tilde{h}} = \frac{L_H}{\sigma}\left(\frac{\psi_{\tilde{h}}}{(P_H^{\text{JV}})^{1-\sigma}} - \frac{\psi_{\tilde{h}}}{P_H^{1-\sigma}}\right) + \frac{L_F \tau^{1-\sigma}}{\sigma}\left(\frac{\psi_{\tilde{h}}}{(P_F^{\text{JV}})^{1-\sigma}} - \frac{\psi_{\tilde{h}}}{P_F^{1-\sigma}}\right) < 0.$$

Thus, $B \equiv -\Delta\Pi_{\tilde{h}} = \Delta\Pi_h + \Delta\Pi_f > 0$ and the negotiating pair's combined operating gain equals the fringe's loss and is strictly positive, so a transfer T always implements the JV. With zero leader bargaining power $T = -\Delta\Pi_h$, giving the leader net payoff $\Delta\Pi_h + T = 0$ and the Chinese firm net payoff $\Delta\Pi_f - T = B$. □

Proof of Proposition 2. Write $\Delta W_H = G + \Delta\Pi_{\tilde{h}}$, where $G = \frac{1}{\sigma-1} \ln\left((P_H^{\text{JV}})^{1-\sigma} / P_H^{1-\sigma}\right)$. Holding other parameters constant, we can write ΔW_H and G as a function of $\psi_{\tilde{h}}$: $\Delta W_H(\psi_{\tilde{h}})$ and $G = G(\psi_{\tilde{h}})$. Then $\Delta W_H(0) = G(0) = \frac{1}{\sigma-1} \ln \frac{1+\tau^{1-\sigma}}{1+\tau^{1-\sigma} b^{1-\sigma}} > 0$ for $b > 1$, and $\Delta W_H \to 0$ as $\psi_{\tilde{h}} \to \infty$, as $\psi_{\tilde{h}}$ becomes large, any effects from the JV becomes negligible.

First, we show that ΔW_H is U-shaped in $\psi_{\tilde{h}}$. Using $\frac{\partial P_H^{1-\sigma}}{\partial \psi_{\tilde{h}}} = \frac{\partial (P_H^{\text{JV}})^{1-\sigma}}{\partial \psi_{\tilde{h}}} = 1$ and $\frac{\partial P_F^{1-\sigma}}{\partial \psi_{\tilde{h}}} =$

$\frac{\partial (P_F^{\mathrm{JV}})^{1-\sigma}}{\partial \psi_{\tilde{h}}} = \tau^{1-\sigma}$, together with the algebraic identities $P_H^{1-\sigma}(P_H^{\mathrm{JV}})^{1-\sigma} - \psi_{\tilde{h}}\left(P_H^{1-\sigma} + (P_H^{\mathrm{JV}})^{1-\sigma}\right) = (1+\tau^{1-\sigma}b^{1-\sigma})(1+\tau^{1-\sigma}) - \psi_{\tilde{h}}^2$ and $P_F^{1-\sigma}(P_F^{\mathrm{JV}})^{1-\sigma} - \tau^{1-\sigma}\psi_{\tilde{h}}\left(P_F^{1-\sigma} + (P_F^{\mathrm{JV}})^{1-\sigma}\right) = 2(\tau^{1-\sigma}+b^{1-\sigma}) - \tau^{2(1-\sigma)}\psi_{\tilde{h}}^2$, term-by-term differentiation yields $\frac{\partial \Delta W_H}{\partial \psi_{\tilde{h}}} = -C(\psi_{\tilde{h}})$, where

$$C(\psi_{\tilde{h}}) = \underbrace{\frac{\tau^{1-\sigma}(1-b^{1-\sigma})}{(\sigma-1)\,P_H^{1-\sigma}(P_H^{\mathrm{JV}})^{1-\sigma}}}_{>0} + \frac{\tau^{1-\sigma}(1-b^{1-\sigma})}{\sigma}\,\frac{(1+\tau^{1-\sigma}b^{1-\sigma})(1+\tau^{1-\sigma}) - \psi_{\tilde{h}}^2}{\left[P_H^{1-\sigma}(P_H^{\mathrm{JV}})^{1-\sigma}\right]^2} + \frac{L_F\,\tau^{1-\sigma}(2-\tau^{1-\sigma}-b^{1-\sigma})}{\sigma}\,\frac{2(\tau^{1-\sigma}+b^{1-\sigma}) - \tau^{2(1-\sigma)}\psi_{\tilde{h}}^2}{\left[P_F^{1-\sigma}(P_F^{\mathrm{JV}})^{1-\sigma}\right]^2}.$$

Because $0 < \tau^{1-\sigma} < 1$ and $0 < b^{1-\sigma} \leq 1$, the prefactors $\tau^{1-\sigma}(1-b^{1-\sigma}) \geq 0$ and $L_F\tau^{1-\sigma}(2-\tau^{1-\sigma}-b^{1-\sigma}) > 0$ are nonnegative and the first term is strictly positive, so $C(\psi_{\tilde{h}}) > 0$ at small $\psi_{\tilde{h}}$: welfare is initially falling. For large $\psi_{\tilde{h}}$, since $\Delta W_H \sim \left(\lim_{\psi_{\tilde{h}}\to\infty}\psi_{\tilde{h}}\Delta W_H\right)/\psi_{\tilde{h}}$, we have $C = -\partial\Delta W_H/\partial\psi_{\tilde{h}} \sim \left(\lim_{\psi_{\tilde{h}}\to\infty}\psi_{\tilde{h}}\Delta W_H\right)/\psi_{\tilde{h}}^2$, so the sign of C at large $\psi_{\tilde{h}}$ equals that of the limit $\Delta W_H \sim \left(\lim_{\psi_{\tilde{h}}\to\infty}\psi_{\tilde{h}}\Delta W_H\right)/\psi_{\tilde{h}}$, which will be computed below. As C changes sign at most once, ΔW_H either decreases monotonically to its limit (if $C > 0$ throughout) or has a single interior trough (if C turns negative).

Each term of ΔW_H decays like $1/\psi_{\tilde{h}}$. Using that $P_H^{1-\sigma}, (P_H^{\mathrm{JV}})^{1-\sigma} \sim \psi_{\tilde{h}}$ and $P_F^{1-\sigma}, (P_F^{\mathrm{JV}})^{1-\sigma} \sim \tau^{1-\sigma}\psi_{\tilde{h}}$, we obtain

$$\lim_{\psi_{\tilde{h}}\to\infty}\psi_{\tilde{h}}\,\Delta W_H = \frac{\tau^{1-\sigma}(1-b^{1-\sigma})}{\sigma(\sigma-1)} - \frac{L_F\,(2-\tau^{1-\sigma}-b^{1-\sigma})}{\sigma\,\tau^{1-\sigma}}, \tag{C.1}$$

whose first term collects the consumer-surplus gain G and the home fringe loss and whose second term is the foreign fringe loss. Writing

$$\bar{L}_F = \frac{\tau^{2(1-\sigma)}\,(1-b^{1-\sigma})}{(\sigma-1)\,(2-\tau^{1-\sigma}-b^{1-\sigma})}$$

for the value of L_F at which (C.1) vanishes, the limit is negative iff $L_F > \bar{L}_F$, and by Step 1 its sign fixes the shape of ΔW_H. If $L_F > \bar{L}_F$, then $C(\psi_{\tilde{h}}) < 0$ at large $\psi_{\tilde{h}}$, so ΔW_H has a single interior trough and is negative for all sufficiently large $\psi_{\tilde{h}}$. If $L_F \leq \bar{L}_F$, then $C(\psi_{\tilde{h}}) > 0$

throughout, so ΔW_H decreases monotonically from $G > 0$ to its nonnegative limit and stays positive at every finite $\psi_{\tilde{h}}$. Hence $\Delta W_H < 0$ for some $\psi_{\tilde{h}}$ if and only if $L_F > \bar{L}_F$. Equivalently, the foreign fringe term is negative and linear in L_F, so ΔW_H is strictly decreasing in L_F at each $\psi_{\tilde{h}}$ and $\inf_{\psi_{\tilde{h}}} \Delta W_H$ crosses zero exactly once, at $L_F = \bar{L}_F$. □

Proof of Proposition 3. Part (i). The maintained assumption $L_F > \frac{\tau^{2(1-\sigma)}}{\sigma-1}$ implies $L_F > \bar{L}_F$, so by the proof of Proposition 2 the limit (C.1) is strictly negative: ΔW_H is U-shaped in $\psi_{\tilde{h}}$ (strictly decreasing, then strictly increasing) and converges to 0 from below. Starting from $\Delta W_H(0) = G > 0$ and ending at 0^-, it therefore crosses zero exactly once—on its decreasing branch, at some $\bar{\psi}_{\tilde{h}}$—and the increasing branch rises toward 0 but remains negative. Hence $\Delta W_H > 0$ on $[0, \bar{\psi}_{\tilde{h}})$ and $\Delta W_H \leq 0$ on $[\bar{\psi}_{\tilde{h}}, \infty)$.

Part (ii). Only $P_H^{1-\sigma}$ and $P_F^{1-\sigma}$ depend on b; since $(P_H^{\mathrm{JV}})^{1-\sigma}$ and $(P_F^{\mathrm{JV}})^{1-\sigma}$ do not, and $\frac{\partial P_H^{1-\sigma}}{\partial b} = \tau^{1-\sigma}(1-\sigma)b^{-\sigma}$, $\frac{\partial P_F^{1-\sigma}}{\partial b} = (1-\sigma)b^{-\sigma}$, the chain rule gives

$$\frac{\partial \Delta W_H}{\partial b} = (1-\sigma)b^{-\sigma}\,\tau^{1-\sigma}\,\Phi(b), \qquad \Phi(b) = -\frac{1}{(\sigma-1)P_H^{1-\sigma}} + \frac{1}{\sigma}\frac{\psi_{\tilde{h}}}{(P_H^{1-\sigma})^2} + \frac{1}{\sigma}\frac{L_F\psi_{\tilde{h}}}{(P_F^{1-\sigma})^2},$$

Since $(1-\sigma)b^{-\sigma}\tau^{1-\sigma} < 0$, $\frac{\partial \Delta W_H}{\partial b} < 0 \iff \Phi(b) > 0$. Grouping the two home terms, with $s_{H\tilde{f}} \equiv \frac{\psi_{\tilde{h}}}{P_H^{1-\sigma}} \in (0,1)$ the fringe's home revenue share,

$$-\frac{1}{(\sigma-1)P_H^{1-\sigma}} + \frac{1}{\sigma}\frac{\psi_{\tilde{h}}}{(P_H^{1-\sigma})^2} = \frac{1}{P_H^{1-\sigma}}\left(\frac{s_{H\tilde{f}}}{\sigma} - \frac{1}{\sigma-1}\right) < 0,$$

since $s_{H\tilde{f}} < 1 < \frac{\sigma}{\sigma-1}$ implies $\frac{s_{H\tilde{f}}}{\sigma} < \frac{1}{\sigma-1}$. Hence the home terms of $\Phi(b)$ are unconditionally negative and a negative comparative static must come from the third foreign term $\frac{1}{\sigma}\frac{L_F\psi_{\tilde{h}}}{(P_F^{1-\sigma})^2} > 0$. Multiplying $\Phi(b)$ by $\psi_{\tilde{h}}$ and letting $\psi_{\tilde{h}} \to \infty$,

$$\lim_{\psi_{\tilde{h}}\to\infty} \psi_{\tilde{h}}\,\Phi(b) = -\frac{1}{\sigma(\sigma-1)} + \frac{1}{\sigma}\frac{L_F}{\tau^{2(1-\sigma)}},$$

which is strictly positive if and only if $L_F > \frac{\tau^{2(1-\sigma)}}{\sigma-1}$. Thus, provided $L_F > \frac{\tau^{2(1-\sigma)}}{\sigma-1}$, $\Phi(b) > 0$ for all $\psi_{\tilde{h}}$ above some threshold, so $\frac{\partial \Delta W_H}{\partial b} < 0$; whereas $\lim_{\psi_{\tilde{h}}\to 0} \Phi(b) = -\frac{1}{(\sigma-1)(1+\tau^{1-\sigma}b^{1-\sigma})} < 0$, so for

small $\psi_{\tilde{h}}$, the sign reverses ($\frac{\partial \Delta W_H}{\partial b} > 0$). □

D. 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:

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

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

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

where $\mathbb{1}[\cdot]$ is an indicator function. By using an indicator function, we generalize equation (5.5) to apply in both cases: $m^F > 0$ and $m^F \leq 0$. A Home leader's value function with JV is

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

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

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

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

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:

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

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

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

$$\dot{\mu}_t(\mathbf{m};\mathcal{J}) = \underbrace{x_{ht}(m^F-1,m^{DH}-1,m^{DF};\mathcal{J})\mu_t(m^F-1,m^{DH}-1,m^{DF};\mathcal{J})}_{\text{Innovation by Home leader}} \tag{D.8}$$

$$+\underbrace{x_{ft}(m^F+1,m^{DH},m^{DF}-1;\mathcal{J})\mu_t(m^F+1,m^{DH},m^{DF}-1;\mathcal{J})}_{\text{Innovation by Foreign leader}}$$

$$+\underbrace{d_{ht}(m^F,m^{DH},m^{DF};0)\mathbb{1}[\mathcal{J}=1]\mu_t(m^F,m^{DH},m^{DF};0)}_{\text{JV investment}}+\underbrace{\chi\mathbb{1}[\mathcal{J}=0]\mu_t(m^F,m^{DH},m^{DF};1)}_{\text{JV exit}}$$

$$+\underbrace{\delta^D\mathbb{1}[m^{DH}=0]\sum_{n=1}^{n=\bar{m}}\mu_t(m^F,n,m^{DF};\mathcal{J})}_{\text{Home domestic diffusion}}+\underbrace{\delta^D\mathbb{1}[m^{DF}=0]\sum_{n=1}^{n=\bar{m}}\mu_t(m^F,m^{DH},n;\mathcal{J})}_{\text{Foreign domestic diffusion}}$$

$$+\underbrace{\delta^F\mathbb{1}[m^F=0]\sum_{n=-\bar{m}}^{n=\bar{m}}\mu_t(n,m^{DH},m^{DF};\mathcal{J})}_{\text{International diffusion}}+\underbrace{\phi\mathbb{1}[m^F=0,\mathcal{J}=1]\sum_{n=-\bar{m}}^{n=\bar{m}}\mu_t(n,m^{DH},m^{DF};1)}_{\text{JV direct diffusion}}$$

$$-\underbrace{\left(x_{ht}(\mathbf{m};\mathcal{J})+x_{ft}(\mathbf{m};\mathcal{J})+2\delta^D+d_{ht}(\mathbf{m})\mathbb{1}(\mathcal{J}=0)+\delta^F+(\phi+\chi)\mathbb{1}(\mathcal{J}=1)\right)\mu_t(\mathbf{m};\mathcal{J})}_{\text{Subtracted mass}}. \tag{D.9}$$

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, domestic and international diffusions. Finally, the last line captures the mass leaving the current state.

D.1 Nash-in-Nash Bargaining

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

$$\begin{aligned} C_t(\mathbf{m}) &= \underset{C}{\operatorname{argmax}} \left\{ \left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi} \times \left(\Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C\right)^{1-\xi} \right\} \\ &\text{s.t.} \qquad \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C \geq 0 \\ &= (1-\xi)\left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C^E\right) - \xi \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) \end{aligned} \tag{D.10}$$

$$\begin{aligned} C_t^E(\mathbf{m}) &= \underset{C^E}{\operatorname{argmax}} \left\{ \left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi^E} \times \left(\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E\right)^{1-\xi^E} \right\} \\ &\text{s.t.} \qquad \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E \geq 0 \\ &= (1-\xi^E)\left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C\right) - \xi^E \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}) \end{aligned} \tag{D.11}$$

Combining equations (D.10) and (D.11), we obtain

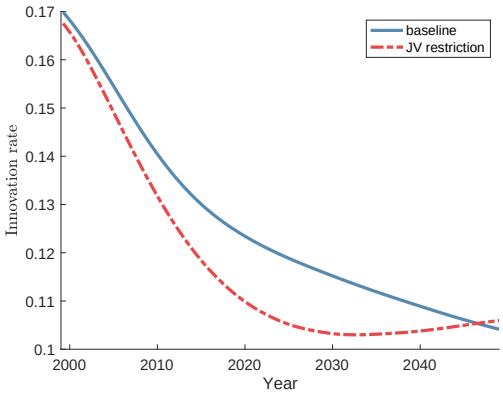
$$C = \frac{\xi^E(1-\xi)}{\xi^E(1-\xi)+\xi}\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \frac{\xi}{\xi^E(1-\xi)+\xi}\Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) \tag{D.12}$$

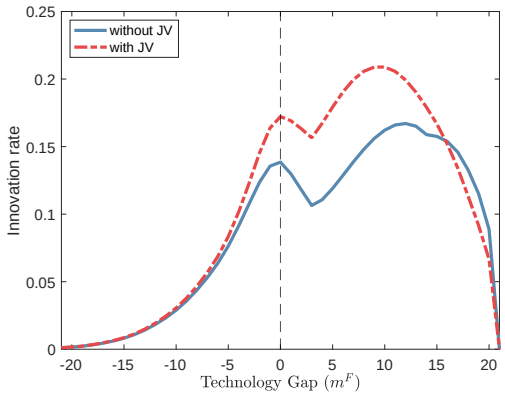
$$C^E = \frac{\xi(1-\xi^E)}{\xi(1-\xi^E)+\xi^E}\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m})\right\} - \frac{\xi^E}{\xi(1-\xi^E)+\xi^E}\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}). \tag{D.13}$$

When we set $\xi^E = 1$, we obtain the expression used for our quantitative analysis on coordinated JV decisions.

D.2 Additional Figures and Tables

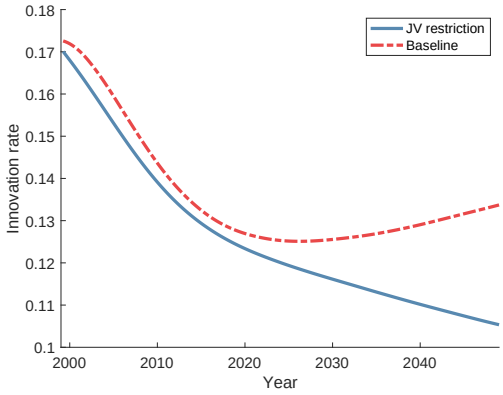
Figure D1: US Innovation Rate over Time and Technology Gap. The Cases of Larger Market Size $\kappa = 1$ and No Direct Diffusion $\phi = 0$

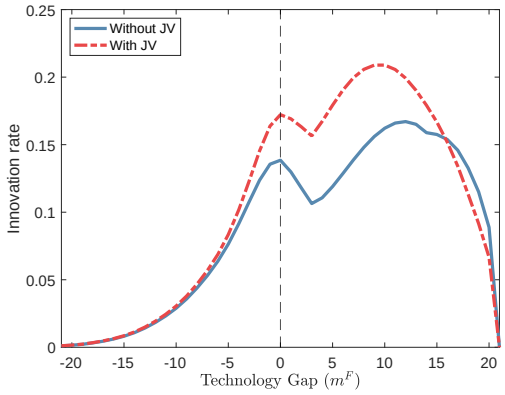




Larger market size effect ($\kappa = 1$)

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. Banning 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	−10.15
Own profit	0.041	0.038	−8.53
JV profit	0.004	0.000	n/a
JV fee payment	−0.003	0.000	n/a
CN fringe profit	0.063	0.059	−5.78
CN labor income	0.895	0.827	−7.56
CN total real income	1.000	0.924	−7.56

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)	0.038	0.036	−4.23
Own profit	0.037	0.036	−1.89
JV profit	0.002	0.000	n/a
JV fee revenue	−0.001	0.000	n/a
US fringe profit	0.066	0.067	0.33
US labor income	0.896	0.879	−1.90
US total real income	1.000	0.982	−1.83

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 Section 7.2. 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. Banning Joint Venture in 1999. Alternative Assumptions

	Δ US Welfare (%)	ΔCN Welfare (%)	Δ US Innovation rate (%)	Δ CN Innovation rate (%)
Baseline	1.07	−8.78	1.14	5.03
No innovation	0.37	−12.52	0	0
Love of variety	0.65	−9.16	1.14	5.03
Constant markup	1.12	−6.18	1.07	3.39

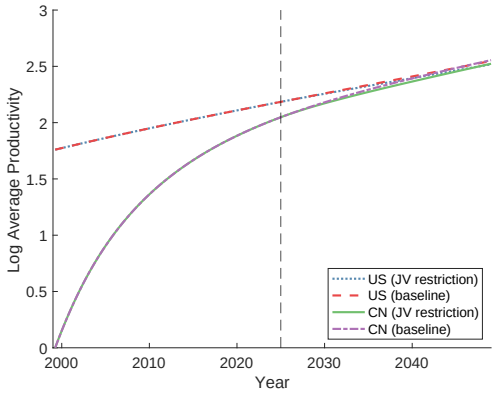
Notes. This table reports the effects of banning JV in 1999 with alternative parameterizations. Δ Welfare is expressed in consumption-equivalent units, and Δ innovation rate denotes the difference in average innovation rates over the first 50 years between the baseline and counterfactual scenarios.

Table D4: Baseline vs. Banning Joint Venture in 1999. Robustness. Sensitivity Checks

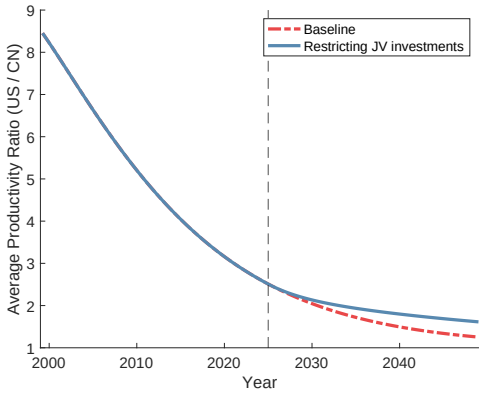
	Δ US Welfare (%)	ΔCN Welfare (%)	Δ US Innovation rate (%)	Δ CN Innovation rate (%)
Baseline	1.07	−8.78	1.14	5.03
	Panel A. Direct diffusion (baseline: $\phi = 0.16$)			
$\phi = 0.1$	0.81	−8.99	0.71	5.32
$\phi = 0.22$	1.14	−8.39	1.39	4.74
	Panel B. International diffusion (baseline: $\delta^F = 0.029$)			
$\delta^F = 0.024$	1.18	−9.70	1.39	5.61
$\delta^F = 0.034$	0.90	−8.12	0.86	4.54
	Panel C. Domestic diffusion (baseline: $\delta^D = 0.029$)			
$\delta^D = 0.024$	1.21	−8.65	1.28	5.16
$\delta^D = 0.034$	0.98	−8.88	1.04	4.93
	Panel D. Initial technology gap (baseline: $b = 20$)			
$b = 23$	1.02	−9.51	0.68	4.60
$b = 17$	0.92	−7.90	1.46	5.40
	Panel E. US JV profit share (baseline: $\kappa = 0.54$)			
$\kappa = 0.75$	0.73	−9.42	0.99	4.90
$\kappa = 0.25$	1.52	−7.84	1.32	5.16

Notes. This table reports the effects of banning 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.

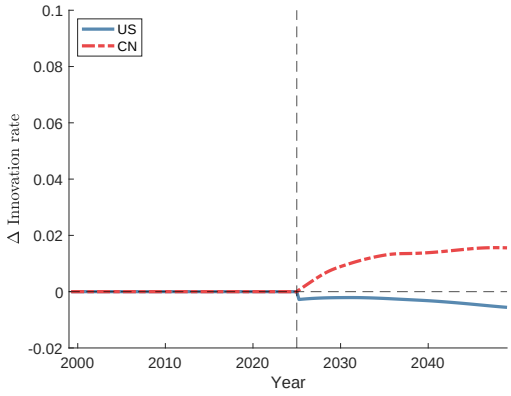
Figure D2: Baseline vs. Banning Joint Venture Investments in 2025: Dynamics of Productivity, Innovation, and Consumption



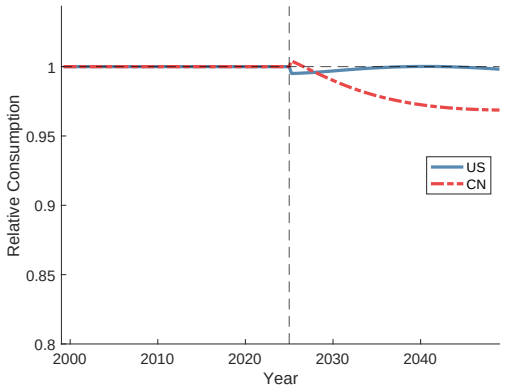
A. Log leader productivity



B. Productivity ratio (US/China)



C. Innovation rate difference



D. Relative consumption

Notes. This figure compares dynamics under the counterfactual (JV ban 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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