Did US Multinationals Transfer Too Much Technology to China?*

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Abstract

Joint ventures provide US firms with access to the Chinese market and cheaper labor, but they also facilitate knowledge spillovers to their partners and other local firms, thereby intensifying future competition from Chinese firms. Although US firms take into account this spillover effect in their joint venture decisions, they do not consider the impact on other US firms. Consequently, there may be over-investment in joint ventures relative to the social optimum for the US. In line with this idea, we establish three novel empirical facts. First, Chinese firms entering into joint ventures experienced growth in size, exports, and technological proximity to their US partners. Second, in industries with a higher number of joint ventures, even non-participating Chinese firms grew larger and achieved technological advancements. Third, US firms in these industries experienced negative impacts, including declines in size, exports, and innovation. We develop a two-country growth model in which oligopolistic firms make decisions regarding innovation and joint ventures. Our quantitative analysis demonstrates that leading US firms tend to over-invest in joint ventures. Banning joint ventures increases welfare in the US by 1 percent, with short-run losses outweighed by long-run gains. The policy reduces welfare in China by more than 9 percent, as it delays Chinese firms' productivity growth.

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1. Introduction

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

However, considering that US firms voluntarily form joint ventures to gain access to the Chinese market despite the risk of technology leakage, is there an economic justification for restricting joint ventures? When US firms establish joint ventures with Chinese firms, they recognize and consider the possibility that these ventures will enhance the productivity of their Chinese partners and other local firms through knowledge spillovers, thereby intensifying global competition in the future. However, they do not consider the dynamic profit losses that other US firms will suffer due to intensified competition. This competition effect from spillovers represents a negative externality from the perspective of the US social planner. There may be too many joint ventures and technology transfers in equilibrium, which can justify a policy restricting joint ventures.[2]

Our paper makes two contributions. First, we provide novel empirical evidence of technology spillover and the negative competition effect resulting from joint ventures. Second, motivated by these findings, we build a two-country endogenous growth model with oligopolistic firms making innovation and joint venture decisions strategically, and we analyze the full dynamics of the model. Our quantitative analysis shows that there are too many joint ventures in equilibrium because leading US firms do not consider the negative competition effect through spillovers on other US firms. Banning joint ventures improves welfare in the US. Below, we discuss these contributions in detail.

For the empirical analysis, we construct our dataset by merging Chinese firm-level balance sheet data from the Census, patent data, and ownership structure information from Orbis. For US firms, we rely on Compustat data. Using this comprehensive dataset, we present three empirical findings on the impact of joint ventures.

First, we find a positive *direct* effect of joint ventures on Chinese partners (or parent firms) using an event study design. Specifically, we match Chinese parent firms that establish joint ventures

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

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

with foreign MNEs (the treated) to firms that have never formed such relationships (the control) through propensity score matching. Following the formation of joint ventures, the Chinese parent firms experienced significant growth in sales, capital, and exports. Furthermore, their patents became more similar to those of their foreign partner firms, indicating a diffusion of knowledge within the joint venture.

Second, we find evidence of *indirect* spillovers to other Chinese firms that are not part of a joint venture. In sectors with more joint ventures, these firms also experienced growth in size and technological advancements. To address endogeneity concerns, we use an instrumental variable (IV) strategy. Our instrument is the changes in joint venture investments from Japan and Korea to India. The identifying assumption is that the push and pull factors driving joint venture investments among these three countries are unrelated to those influencing US-China joint ventures.

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

Motivated by these findings, we develop a two-country growth model in which oligopolistic firms make forward-looking, strategic decisions on innovation and joint ventures. There are two types of firms in each country: leaders and fringe. All firms from both countries produce varieties and export to foreign markets. Leaders can enhance productivity through innovation and have the option to establish joint ventures in the other country, in partnership with a foreign leader firm. These joint ventures enable firms to bypass trade costs and produce using the other country's workers. The profits from joint ventures are shared between the home and foreign leader firms through Nash bargaining.

Even without joint ventures, the model allows for stochastic knowledge diffusion both within and between countries. Once a joint venture is established in the foreign country, the probability of knowledge diffusion from the home leader firm to the foreign leader firm (the parent of the joint venture) increases, consistent with our first empirical finding on the direct effect. In addition, fringe firms in the foreign country can also improve their productivity through knowledge spillovers from the joint venture and the foreign parent firm, which aligns with our second empirical finding on the indirect effect.

The entry of the new joint venture firm immediately intensifies competition in the market. The knowledge spillovers to the foreign leader (the parent of the joint venture) and the foreign fringe further intensify competition over time. The home leader (the parent of the joint venture) takes all these effects into account when making the joint venture decision. It also partially captures the profits of the joint venture and the spillover benefits to the foreign leader through bargaining. However, it ignores the negative effects of heightened competition on the profits of its domestic competitor (the home fringe). Our third empirical finding above confirms this negative effect.

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

Using the calibrated model with joint ventures, we calculate the effect of a policy that completely bans joint ventures. We find that shutting down joint ventures increases welfare in the US by 1.0 percent and decreases welfare in China by 9.1 percent, in units of permanent consumption. This is because the US can maintain its technological leadership longer due to reduced knowledge spillovers to China. In fact, firms innovate more without joint ventures in both the US and China. For US leaders, the reduced probability of spillovers implies that the profits from successful innovations are larger and longer-lasting. Chinese leaders make up for reduced spillovers by increasing their own innovation efforts. Since US firms cannot immediately benefit from lower wages in China and lower trade costs through joint ventures and must spend more on innovation, the US is negatively affected by the ban in the short run. However, the increased innovation pays off in the longer run, leading to a positive net present value.

As the short-run and long-run effects differ, economic actors in the US are affected differently by the policy. US leader firms' profits decline by 22 percent in present value terms, as labor costs and innovation costs are higher in this policy scenario and they cannot avoid the trade costs through joint ventures. The fringe firms' profits are 6 percent higher in present value terms, as their productivity relative to Chinese competition remains higher for longer in this scenario. Real wages are 2 percent higher, as more production in the US implies higher demand for labor.

To better understand which source of inefficiency matters for the quantitative result, we consider an alternative scenario in which US leader firms must compensate US fringe firms for their losses when establishing joint ventures. In this case, significantly fewer joint ventures are formed. Moreover, banning joint ventures in this setting actually decreases US welfare, suggesting that the failure to internalize the profit losses of other US firms is a key source of inefficiency in joint venture decisions.

Related literature. We contribute to several strands of the literature.

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

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

Third, our empirical findings contribute to the empirical literature on the knowledge diffusion through FDI, which has been reviewed by Harrison and Rodríguez-Clare (2010). Our evidence of the direct effects on Chinese joint venture parent firms is consistent with Jiang et al. (2023) and Bai et al. (2020). It is also consistent with previous literature that studies within-firm knowledge diffusion channels. Our indirect spillover effects to Chinese firms that do not participate in joint ventures are consistent with previous papers that document positive spillovers from foreign MNEs to domestic firms in host countries.[3] In addition to these findings, we provide novel evidence on indirect negative competition effects of US MNEs' joint ventures on other US firms.[4]

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

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

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

declines in US manufacturing employment and innovation.[5]

2. Background and Data

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

After decades of isolation from the West, Deng Xiaoping initiated economic reforms and opening China's markets and foreign investment in 1979 with the "Law on Sino-Foreign Equity Joint Ventures" (henceforth referred as the JV Law). JVs were defined as firms with mixed ownership between foreign and Chinese shareholders, with foreign equity shares between 25% and 100%. Firms with foreign equity below 25% were classified as domestic firms, while those with 100% foreign equity were registered as wholly foreign-owned enterprises (WFOEs). A key difference between JVs and WFOEs is ownership and control. WFOEs are 100% owned and controlled by foreign MNEs, granting them full autonomy over operations and decision-making. In contrast, JVs require shared ownership between foreign MNEs and local Chinese partners. Foreign firms were often required to transfer technology to their local partners, and profits from JVs were shared based on equity stakes. Equity shares were strictly regulated, with minimum requirements and maximum caps on foreign MNE ownership.

The quid pro quo policy emerged alongside JVs, requiring foreign MNEs to transfer technologies, capital equipment, know-how, and product lines as part of their equity contribution (the quid) in exchange for access to China's vast consumer market, abundant labor, and natural resources (the quo).[6] From 1979 to 1986, JVs were the only legally permitted form of FDI in China, although WFOEs were gradually allowed in some sectors starting in 1986. Following China's WTO accession in 2001, the Chinese government introduced major FDI policy reforms, along with tariff liberalization and enhanced intellectual property protections, to comply with WTO obligations. Notably, explicit technology transfer requirements were prohibited, and overall JV requirements were relaxed.[7] However, in many high-tech related sectors, equity restrictions and JV requirements persisted.[8]

Despite these post-WTO reforms, concerns over the quid pro quo policy have not been entirely alleviated by the US policymakers. The US government has argued that these policies have persisted in more implicit forms and has criticized them as unfair trade practices. This criticism intensified with

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

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

[7] For example, in 1995, the State Council of China published the "Guiding List of Industries for Investments by Foreign Businessmen," which outlined industries open to JV investments and imposed restrictions on foreign ownership shares. The list underwent multiple revisions between 1995 and 2017, with a major update in 2002 following China's WTO accession.

[8] Since 1995, "Catalogue for the Guidance of Foreign Investment Industries" (henceforth the Catalogue) provided guidelines for regulations on FDI (Brandt et al., 2017; Lu et al., 2017; Eppinger and Ma, 2024). Although this Catalogue became more liberal with revisions in 1997, 2002, 2004, 2007, and 2012, still many high-tech sectors or sectors related to national security were subject to the regulation. For example, in 2017, in the automobile industry, the Chinese partner's ownership share could not fall below 50%. Airplane manufacturing was restricted to joint ventures, while rare earth exploration, mining, and processing remained completely closed to foreign investment.

China's rapid growth, being the second largest economy, and the launch of "Made in China 2025", an industrial policy introduced in 2015 to accelerate the development of China's high-tech industries. This initiative raised national security concerns and fears of global economic rivalry among US policymakers, who argue that China's continued quid pro quo policy remains central to its industrial strategy, particularly in high-tech sectors.

In fact, the quid pro quo policy was cited as one of the key motivations behind the US-China trade war by the Office of the United States Trade Representative (USTR). The USTR, in its Section 301 Investigations (2017–2018), reported that China implicitly pressured foreign MNEs to form JVs and share advanced technologies through regulatory pressures and informal administrative barriers. In response to these concerns, the US initiated the trade war with China in 2018, imposing tariffs on over $250 billion worth of Chinese goods. Also, the Biden administration further tightened restrictions on Chinese firms' access to critical US technologies by expanding the Entity List and banning recipients of CHIPS ACT funding from making certain investments in China.

2.2 Data

We construct the main dataset by merging balance sheet, ownership structure, and patent data for Chinese and U.S. manufacturing firms, along with sectoral data, covering the period 1998-2013.

Chinese firm balance sheet. We obtain Chinese firm balance sheet from the census of Chinese manufacturing firms, Annual Survey of Industrial Enterprises, constructed by the National Bureau of Statistics which collects annual information of all state-owned and private firms with sales exceeding 5 million Renminbi before 2010 and 20 million since 2011. The data includes information on firms' sales, exports, employment, and capital (measured as fixed assets), along with their affiliated industry (4-digit CIC code) and location.[9] The data is representative at the national level, which accounts for 90% of total Chinese manufacturing output. The dataset has information on firm registration types including JVs, WFOEs, state-owned firms, and domestic private firms. In our definition of JVs and WFOEs, we exclude those involving foreign MNEs from Hong Kong, Macao, and Taiwan, given the special economic and regulatory relations between China and these regions.

US firm balance sheet. We obtain US firm balance sheet from US Compustat that covers publicly listed firms in the US, including sales, employment, capital (measured as PPEGT), and R&D expenditures. We also obtain each firm's total foreign sales (including both exports and sales from foreign affiliates) from the historical geographic segment data and use this variable as a proxy for exports.[10] A firm's industry affiliation is classified under 4-digit 1987 SIC codes. We aggregate these codes follow-

[9] To ensure consistent 4-digit CIC codes across the sample period, we use concordance tables from the Industrial Classification for National Economic Activities and the CIC 1994-CIC 2002 concordance table by Brandt et al. (2012). Brandt et al. (2012) provides a more detailed description of the dataset.

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

ing Autor et al. (2013) and further consolidate them into 383 4-digit codes to ensure compatibility with the 4-digit Chinese Industry Code (CIC) in the Chinese firm balance sheet data and the HS codes.

Ownership structure. Although the Annual Survey of Industrial Enterprises identifies whether firms are FDI affiliates (JVs or WFOEs) or not, it does not have information on their ownership shares between Chinese partners and foreign MNEs. To identify these shares, we use historical ownership data from the Orbis Global database, one of the largest databases of public and private firm information. 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.[11]

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

Sectoral and trade data. We obtain sectoral data for US manufacturing from the NBES-CES manufacturing database and bilateral trade data from CEPII (Gaulier and Zignago, 2012) and Comtrade.

3. Motivating Facts

In this section, we present three motivating facts on JV: direct effects of JV formation on Chinese partners, indirect positive spillover effects to other Chinese firms, and indirect negative competition effects on US firms. While the direct effects arise from Chinese partners benefiting from JV formation with foreign MNEs, the indirect positive spillovers refer to other Chinese firms gaining from JVs without direct involvement. The indirect negative competition effects on US firms capture how Chinese firms' performance improvements—whether through direct benefits or indirect spillovers—weakened US firms' competitiveness.

Fact 1. Direct Effects of JV Formation on Chinese Parent 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 their first JV formation. A key concern is endogeneity due to selection into JV formation. To address this, 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 probit model

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

with firm-size related observables as covariates. These include log sales, log capital, log employment, dummies of exporting and positive patent stock, inverse hyperbolic sine transformation of exports and patent stock, and year fixed effects. For each treated firm, we match a control firm from the same year and 2-digit industry with the closest propensity score, allowing replacements so that a control firm can be matched to multiple treated firms.

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

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

where i denotes firm, m match, and t year. y_{imt} is an outcome variable of interest. D_{mt}^{τ} are event study dummies defined as $D_{mt}^{\tau} \equiv \mathbb{1}[t - \tau = t(m)]$, where $t(m)$ is the event year of match m. $\mathbb{1}[\text{JV Partner}_{it}]$ is a dummy for forming first JVs. We normalize β_{-1} to zero. δ_{im} and δ_{mt} are match-firm and match-year fixed effects. ε_{imt} is an error term. Standard errors are two-way clustered at the match and firm levels, which accounts for mechanical correlations in residuals introduced by matching with replacement, as the same firm may appear multiple times. The specification is fully-stacked event study design (Cengiz et al., 2019) that does not suffer from issues studied by the recent staggered diff-in-diff literature (e.g. Roth et al., 2023).

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

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

$F_{imt} = (p_{i1t}, \ldots, p_{iKt})^{\top}$ is a vector where the k-th element represents Chinese firm i's patent stock (under the Chinese patent system) in k-th technological fields within match m and year t. Similarly, $F_{\text{MNE},t(m)}$ represents foreign MNEs' patent stock from the USPTO, measured at the event year $t(m)$, making it time-invariant.[12] We use different patenting systems for Chinese partners and foreign MNEs because Chinese firms rarely patent with the USPTO, while the U.S. patent system serves as a better measure for the technological frontier of MNEs. Higher values indicate greater technological

[12] When calculating proximity, we assign greater weight to more recent patents by applying an R&D depreciation rate of 0.3 (Li and Hall, 2020). Specifically, we compute F_{imt} as: $F_{imt} = \text{New patent}_{imt} + 0.7 \times F_{im,t-1}$, where New patent_{imt} is a vector of new patents across technological fields.Our results remain robust to alternative depreciation rates ranging from 0 to 0.5 (cols. 7-9 of Appendix Table A4). Similar measures have been used in prior studies to calculate technological proximity between firms (e.g. Branstetter, 2006; Bloom et al., 2013; Akcigit et al., 2016).

proximity between Chinese firms and MNEs, as patents reflect their technological capabilities.

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

The matched treated and control groups are well-balanced across observable characteristics, including various size measures, labor productivity, patenting activity, and exporting status (Appendix Table A1). Furthermore, a balance test—regressing the treatment dummy on these pre-event observables—confirms that none of these observables significantly predict treatment status (Appendix Table A2). Additionally, raw data plots reveal no differential pre-trends between the two groups before the event. The outcomes of the two groups started to diverge only after the event, exhibiting the parallel trends before the event (Appendix Figure A1).

For these estimates to admit causal interpretations, treatment status must be exogenous, and both groups should follow the same pre-trend before the event. While matching based on observables may not fully eliminate biases due to unobserved factors, the event study provides useful descriptive evidence on the impact of JV formation on Chinese partners.

Estimation results. Figure 1 reports the results (see cols. 1-4 of Appendix Table A3 for more details). 4 years after forming JVs for the first time, Chinese partners' sales and capital increased by 27% and 35%, with improvements in export performance. Importantly, they technologically became close to their foreign MNE counterparts. These findings suggest that their improved performance could be attributable to technological learning from foreign MNEs.

We consider a battery of robustness checks. Forming JVs also had positive impacts on alternative outcomes including log employment, export dummies, cumulative patents and yearly new patents (cols. 5-8 of Appendix Table A3). The results remain robust to mild violations to the parallel pre-trend assumption, except for exports, based on the methodology developed by Rambachan and Roth (2023) (Appendix Figure A2). The results are also robust to alternative numbers of matches (cols. 1-6 of Appendix Table A4).

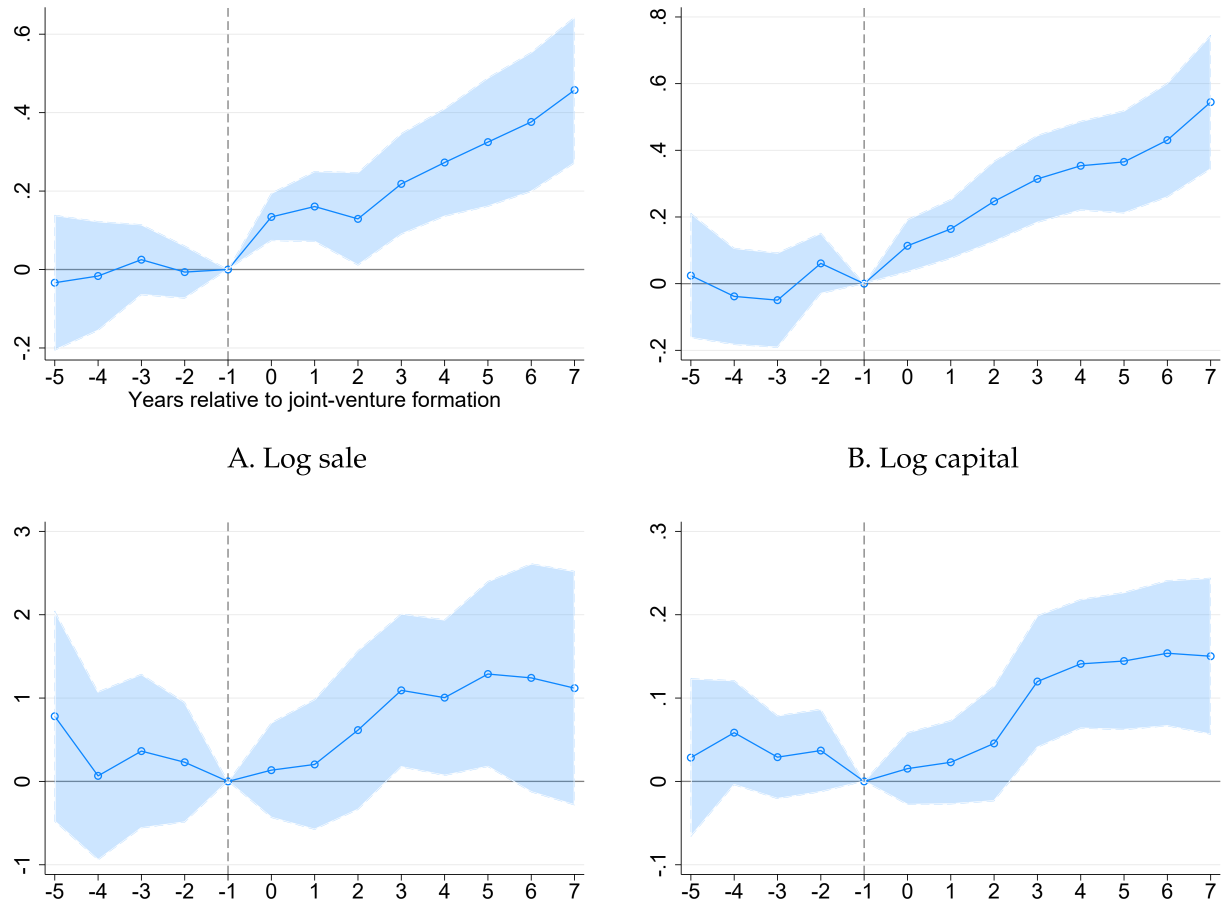
Fact 2. Indirect Positive Spillovers to Chinese Firms

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

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

where f denotes for firm and j CIC or SIC 4-digit industry. The dependent variable Δy_{fj} is the DHS growth rates (Davis et al., 1998) of firm-level outcomes: $100 \times \frac{y_{fj,12} - y_{fj,99}}{0.5(y_{fj,12} + y_{fj,99})}$. $\mathbf{X}_{fj}$ are observables. All

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



A. Log sale

B. Log capital

C. Ihs export

D. Technological proximity

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

specifications include dummies of state-owned firms and FDI affiliates, and province fixed effects. ε_{fj} is the error term. Regression models are weighted by firms' initial sales. Standard errors are clustered at the 3-digit industry level.

ΔFDI_{fj} measures sectoral FDI exposure in China. We focus on the total indirect effects of FDI rather than distinguishing between JVs and WFOEs for two reasons. First, conceptually, the negative competition externality applies to both, despite their differences in ownership structure. While only JVs involve local Chinese partners, meaning the direct effects documented above pertain solely to them, both JVs and WFOEs may generate indirect spillovers to other Chinese firms. Whether knowledge diffusion occurs only through indirect spillovers (WFOEs) or through a combination of direct and indirect spillovers (JVs), the externality arises when foreign MNEs fail to internalize other firms' profit losses.[13] Second, separating these effects is econometrically challenging, as it requires exogenous variation for both FDI types, which is typically difficult to obtain. Because our IV strategy, detailed below, exploits exogenous variation in total FDI, we focus on their combined effects instead.

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

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

where $\mathcal{J}^{\text{CN}}_{(-f)jt}$ is a set of sector j FDI affiliates in China in year t owned by MNEs, excluding those from Hong Kong, Macao, and Taiwan.[14] To rule out mechanical correlations, we exclude any FDI affiliates related to firm f in the numerator, denoted as $-f$. If f is a Chinese partner, we exclude all JV affiliates in which f holds ownership. If f is a JV affiliate, we exclude all JV affiliates that share the same Chinese parent.[15] One issue is the concordance between CIC and SIC codes, as a single 4-digit CIC code often maps to multiple SIC 4-digit codes. Therefore, we first construct the sectoral shock at the SIC 4-digit level, as most datasets (except for the Chinese firm balance sheet) are in SIC codes. Then, for CIC codes with multiple SIC mappings, we take a weighted average. Appendix Section A.1 provides further details.

To isolate effects of the FDI shocks from changes in trade policies post-WTO, we include NTRgap_j that measures reductions in trade policy uncertainty between the US and China due to the granting of Permanent Normal Trade Relations (PNTR) post-WTO (Pierce and Schott, 2016), defined as the increase in US tariffs on Chinese goods in case of a failed annual renewal of China's Normal Trade Relations (NTR) status prior to granting the PNTR.[16] It has been well-documented in the trade literature that such reductions measured by the NTR gap contributed to declines in US manufacturing (e.g. Pierce and Schott, 2016; Handley and Limão, 2017).

IV Strategy. The naive OLS estimates can be biased due to endogeneity as unobservable shocks may affect both FDI flows to China and firm growth simultaneously. Pull factors of FDI flows into China include positive demand and productivity shocks in China, while the push factors from the US include rising labor costs. Reductions in unobservable bilateral trade costs between the two countries can also be a source of endogeneity, as MNEs may enter China to serve the large US market.[17] The

[13] For discussions on modes of FDI, see Nocke and Yeaple (2007); Kesternich and Schnitzer (2010) for theoretical analysis and Javorcik and Spatareanu (2008) for empirical evidence.

[14] Aitken and Harrison (1999), Lu et al. (2017), and Jiang et al. (2023) used similar exposure measures to FDI in contexts of Venezuela and China.

[15] For JV affiliates with multiple Chinese parents, we exclude all affiliates linked to each parent.

[16] We obtain the SIC 4-digit level NTR gap from Che et al. (2022). Specifically, NTRgap_j is computed for each four-digit SIC code based on ad valorem equivalent tariff rates for 1999: $\text{NTRgap}_j = \text{Non NTR Rate}_{j,99} - \text{NTR Rate}_{j,99}$.

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

direction of the bias is ex-ante ambiguous. For example, positive demand shocks in China could lead US firms to increase their FDI in China, while also fostering the growth of Chinese firms, leading to an upward bias. On the other hand, higher cost shocks in the US might cause US firms to conduct more FDI in China to lower production costs, while simultaneously decreasing Chinese firms' sales growth through increased competition within China, resulting in a downward bias. Measurement error in the FDI shock is another potential source for a downward bias.

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

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

$\mathcal{J}^{\text{IN,JP-KR}}_{jt}$ is the set of FDI affiliates in India associated with MNEs from Japan or South Korea. We obtain data on Indian firms' balance sheets and ownership from the Prowess database, supplemented with the ownership information from Orbis.[18] The dataset covers over 70% of the Indian manufacturing sector and is representative of large and medium-sized firms. While it may exclude some small firms, this is unlikely to be a major concern, as we focus only on the sales of FDI affiliates in India, which are typically larger than domestic Indian firms. Using the ownership information, we identify the FDI affiliate status of MNEs from Japan and South Korea.

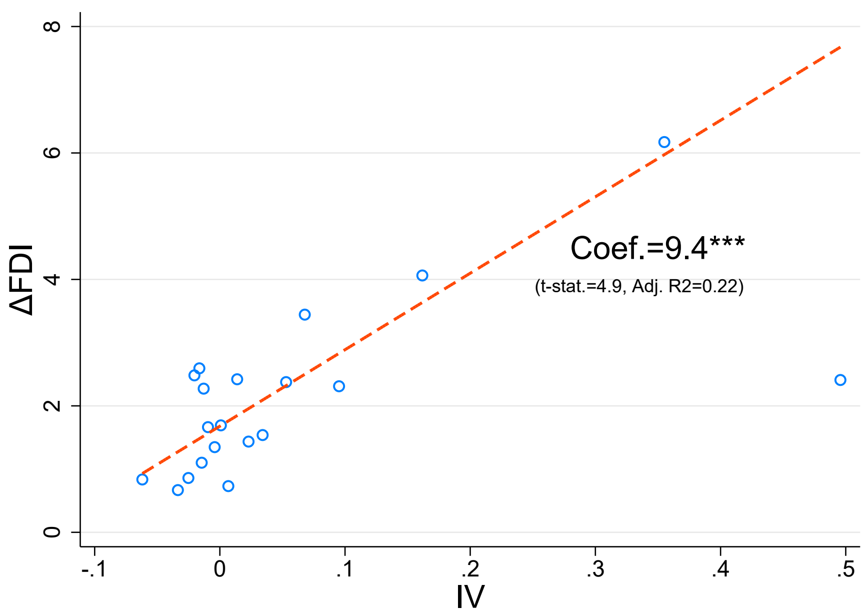
The idea behind the IV is as follows. The IV strategy aims to isolate variation in China's FDI exposure that is plausibly exogenous to factors specific to the US and China. For example, consider exogenous productivity shocks in Japan or South Korea that drive increased FDI flows. By using the Iv based on FDI affiliates in India, we extract these exogenous shocks of the two countries. The explicit identifying assumption is that any unobservables that influence US FDI in China are uncorrelated with the IV. We choose India for its attractiveness to FDI, similar to China, due to its large market size, low wages, and strong economic growth potential, as reflected in the term BRIC.[19] Moreover, excluding the US, Japan and South Korea were the two largest sources of FDI in China.

Figure 2 presents a binscatter plot of the first-stage relationship at the SIC 4-digit level, showing a significantly positive relationship between the FDI shock and IV. The estimated linear-fit coefficient is 9.4, with a t-statistic of 4.9 and an adjusted R-squared of 0.22. The magnitude aligns with the fact that China's total FDI inflows were approximately 10 times larger than India's. The most exposed industries to FDI were machinery and motor vehicle-related sectors.

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

[19] BRIC stood for Brazil, Russia, India, and China—a term to describe a group of emerging economies with high growth potential.

Figure 2: First-Stage Relationship between the FDI Shock and the IV



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

Threats to identification. Before presenting the estimation results, we briefly discuss two potential threats to identification: export platform and technological changes.[20] Regarding the export platform concern, 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 would be violated if China- or US-driven demand shocks influenced FDI flows into India from Japan and South Korea.[21]

The second concern is technological changes that are skill-biased (e.g. Acemoglu et al., 2015; Aum et al., 2018; Aum and Shin, 2025) or reduces communication costs between headquarters and affiliates (e.g., computerization and advances in telecommunication technology) (e.g. Keller and Yeaple, 2013). These shocks may make certain sectors more attractive for FDI, potentially correlating FDI by MNEs in advanced economies like the US, Japan, or South Korea, thus violating the exclusion restriction.

[20] Another potential concern is that globalization trends in liberalization of trade and FDI could make policy reforms in China and India be correlated. However, this is unlikely, as India's major trade and FDI reforms were implemented in 1991, with WTO accession in 1995, about six years before China (Sivadasan, 2009; Goldberg et al., 2010; Bau and Matray, 2023). By taking differences between 1999 and 2012, the IV effectively removes the effects of India's reforms, which had already been in place by 1999.

[21] Large demand shocks in South Korea or Japan could also drive US MNEs to enter China to serve those markets. However, in this case, the IV and FDI shock would exhibit a negative correlation, which contradicts the positive first-stage relationship observed in Figure 2.

We test these concerns by inspecting pre-trends and industry-level balance, following Borusyak et al. (2022) and Goldsmith-Pinkham et al. (2020). First, Panel A reports the pre-trend results. We find that pre-1999 5 year growth (1993-1998) in industry-level variables are not meaningfully correlated with the IV. Although there is a weak positive correlation between gross output and employment at the 10% significance level, these relationships are inconsistent with the expected improvements in Chinese firms' performance and the negative competition effects on US firms. Moreover, growth in producer price indices (PPI), overall imports (excluding China, India, Japan, and South Korea), and imports from China do not show any pre-trends. To further validate these results, we also examine pre-trends using US firm-level data and find no significant correlation between the pre-1999 5-year growth of firm-level outcomes and the IV (Appendix Table A5).[22]

Panel B reports the industry-level balance. The export platform is unlikely to be a significant concern, as there is no significant correlations between bilateral import penetration (import-to-domestic absorption ratio) and the IV for China, India, and the US. Moreover, sectors with higher IVs are not necessarily those in which China initially had higher productivity or those more exposed to FDI, as evidenced 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. These findings further support the the no pre-trend in Panel A. While our research design does not require sectors to be identical in levels, the similarity in these variables supports the plausibility of the exclusion restriction.

We also consider variables related to technological changes.[23] Three variables are significantly correlated with the IV: overall US import penetration (excluding China, India, Japan, and South Korea), production workers' share of employment, and computer investment share. These correlations suggest potential sensitivity to omitted variable bias from unobservable technological changes in labor-intensive sectors, which are 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 pre-trends in Panel A, which we do not observe. To further address this, we test the sensitivity of our estimates by including these controls in the regression.

Estimation results. Table 2 presents the results. In column 1, both OLS and IV estimates are positive and statistically significant at the 1% level. The IV estimate has a larger magnitude than the OLS estimate, indicating that a 1 percentage point increase in the FDI shock led to an 8.97 percentage point increase in sales growth, with the strong first-stage. In column 2, we include three additional variables that showed significant correlations with the IV in the balance test (Table 1) and 1-digit industry dummies. The coefficients remain stable within one standard error of the estimate without the controls. In columns 3-8, the FDI shock also had positive effects on the DHS growth rates of

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

[23] Sectoral R&D intensity is calculated as the mean of firms' R&D intensities within sectors using Compustat data. High-tech and computer investment shares at the SIC 3-digit level are obtained from Acemoglu et al. (2016).

Table 1: Pre-trend and Shock Balance Test of the IV

Balance variable	Coef.	SE	p-val.
Panel A. Pre-trend			
Δ Log gross output, 1993-1998	0.11	(0.06)	[0.06]
Δ Log emp., 1993-1998	0.10	(0.06)	[0.10]
Δ Log PPI, 1993-1998	0.05	(0.05)	[0.35]
Δ US import (ex. CN, IN, JP, SK) / absorption, 1996-1998	0.04	(0.02)	[0.12]
Δ US-CN import / absorption, 1996-1998	−0.04	(0.07)	[0.54]
Panel B. Industry-level balance			
US-CN import / absorption 1996	−0.06	(0.05)	[0.20]
US-IN import / absorption 1996	−0.01	(0.01)	[0.28]
CN-IN import / absorption 1996	−0.02	(0.01)	[0.15]
IN-CN import / absorption 1996	−0.02	(0.02)	[0.25]
JV sales share 1998	0.04	(0.04)	[0.28]
Number of JV firms to total number of firms ratio 1998	0.01	(0.01)	[0.22]
US import (ex. CN, IN, JP, SK) / absorption 1996	0.14	(0.04)	[0.00]
Ratio of capital to wage-bills 1993	−0.07	(0.05)	[0.18]
Ratio of wage bills to value-added 1993	0.03	(0.05)	[0.56]
R&D intensity 1993	0.00	(0.01)	[0.81]
Production workers' share of employment 1993	0.27	(0.06)	[0.00]
High-tech investment shares 1990	−0.13	(0.09)	[0.15]
Computer investment shares 1990	−0.18	(0.05)	[0.00]
N		383	

Notes: Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS estimates obtained after regression industry-level characteristics on the IV. Each observation is a 4-digit SIC industry. All variables are standardized. All regressions are weighted by the initial sector gross output.

capital, employment, and exports.[24] The NTR gap had positive effects on Chinese firms, although these estimates are less precise. Overall, the OLS estimates are downward biased, likely due to measurement errors in the FDI shocks; however, this bias falls within one standard error of the IV estimates.

Evidence of quality/productivity upgrading. We further provide evidence that Chinese firms' improvements in size and export performance were associated with their quality/productivity upgrading. We regress changes in measures of this upgrading on the FDI shock, reported in Table 3. In columns 1-2, the outcomes are DHS growth rates of cumulative patents and wages per employment, commonly used proxies for innovation outcomes (e.g. Aghion et al., 2024; Autor et al., 2020) and skills of workers (e.g. Verhoogen, 2023). Since 2008, the Chinese government implemented a "high-tech" cer-

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

Table 2: Indirect Positive Spillovers to Chinese Firms

Dep. var.	ΔSale		ΔEmp.		ΔCapital		ΔExport	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. OLS							
ΔFDI_{fj}	8.97***	7.47***	7.30***	7.25***	8.89***	7.19***	19.91***	16.71***
	(1.73)	(2.03)	(1.40)	(1.56)	(1.79)	(1.84)	(3.37)	(3.01)
NTRgap_j	−0.08	0.10	0.55*	0.65**	0.15	0.18	1.28*	1.07*
	(0.32)	(0.34)	(0.29)	(0.27)	(0.29)	(0.29)	(0.73)	(0.65)
	Panel B. IV							
ΔFDI_{fj}	12.16***	8.98***	10.31***	10.89***	12.40***	10.04***	23.77***	19.60***
	(3.34)	(2.92)	(2.34)	(2.16)	(3.05)	(2.77)	(5.37)	(4.29)
NTRgap_j	0.03	0.15	0.65**	0.78***	0.27	0.28	1.45*	1.20*
	(0.32)	(0.35)	(0.29)	(0.27)	(0.28)	(0.29)	(0.76)	(0.67)
KP-*F*	45.75	42.22	45.75	42.22	45.75	42.22	45.37	41.85
Add. ctrl.		✓		✓		✓		✓
Mean dep. var.	79.61	79.61	−7.08	−7.08	38.83	38.83	50.60	50.60
# clusters	157	157	157	157	157	157	155	155
N	14844	14844	14844	14844	14844	14844	8491	8491

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

tification policy, granting tax credits to firms meeting standards for intellectual property and R&D.[25] We use dummies of whether firms ever received the "high-tech" status between 2008-2024, obtained from Macrodatas, as as an outcome in column 3. In columns 4-7, the outcomes are DHS growth of the number of exporting/importing products/countries, which have been well-documented to have positive relationships with firm-level quality/productivity in the international trade literature (e.g. Bernard et al., 2011; Manova and Zhang, 2012; Manova and Yu, 2017).[26] The FDI shock had positive

[25]The policy requires firms to obtain the ownership of the intellectual property rights that play a core supporting role in the technology of its main products (services) through independent research and development, assignment, donation, merger and acquisition, etc. See Table 1 of Chen et al. (2023b) for more details on these standards.

[26]Changes in the numbers of exporting/importing products/countries from 2000 to 2013 are obtained from the Chinese Customs Trade Statistics and then matched with our main dataset. The customs records and our Chinese firm balance sheet data do not share common firm identifiers, so following standard practices (e.g. Wang and Yu, 2013; Tian and Yu, 2017; Chor et al., 2021), we merge these two datasets using firm names, phone numbers, and addresses. Changes are measured from 2000 to 2013 due to data unavailability for 1999 and 2012 in the customs data.

Table 3: Evidence of Quality Upgrading of Chinese Firms

Dep. var.	Δ cumulative patent	ΔWage per emp	Dum gvnt high-tech	Δ # export prod	Δ # export cty	Δ # import prod	Δ # import cty
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔFDI_{fj}	3.09**	2.51***	4.36***	25.25***	23.09***	10.55***	13.65***
	(1.43)	(0.83)	(1.41)	(2.88)	(3.18)	(3.65)	(3.22)
NTRgap_j	0.58*	0.02	0.13	1.81***	1.55***	1.95***	1.91***
	(0.30)	(0.16)	(0.11)	(0.43)	(0.41)	(0.36)	(0.40)
KP-*F*	60.98	45.14	45.75	31.29	31.30	35.41	35.41
Mean dep. var.	172.28	120.54	18.97	36.30	33.77	−24.95	−7.21
# clusters	157	157	157	153	153	154	154
N	6628	14817	14844	7316	7312	6414	6410

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

impacts on these variables.

There can be multiple potential channels behind such indirect spillovers. First, these results can reflect knowledge diffusion from MNEs to other firms, for example, through labor mobility. Second, FDI affiliates would likely to provide larger demand and cheaper supply sources for other domestic firms (e.g. Alfaro-Ureña et al., 2022), providing stronger incentives for quality/productivity upgrading. Setzler and Tintelnot (2021) also find similar indirect positive spillovers of FDI in the US.

Fact 3. Indirect Negative Competition Effects to US Firms

Next, we examine the indirect negative competition effects on US firms. Analogous to the indirect positive spillovers for Chinese firms, we estimate the same regression model as in equation (3.3), but with US firms' outcomes as the dependent variables. In contrast to Chinese firms, we expect the coefficients of the FDI shock to be negative, as Chinese firms that directly or indirectly benefited from FDI capture more market share from US firms in the global market. When constructing the FDI shock, for each US MNE, Chinese FDI affiliates associated with it are excluded from the numerator of the FDI shock.[27] Standard errors are clustered at the SIC 3 digit level.

Table 4 reports the results. Column 1 reports the OLS and IV estimates. Both estimates are significantly negative at the 1% level. The IV estimate implies that a one percentage point increase in the

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

Table 4: Indirect Negative Competition Effects to US Firms

Dep.	ΔSale		ΔEmp.		ΔCapital		ΔExport		ΔR&D		ΔPatent	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. OLS												
ΔFDI_{fj}	−11.27***	−9.54***	−10.75***	−8.12***	−12.97***	−9.42***	−8.25*	−7.02**	−10.43**	−6.55**	−0.26	−0.91
	(2.95)	(1.79)	(3.32)	(2.30)	(2.76)	(2.63)	(4.17)	(3.47)	(4.20)	(2.97)	(1.53)	(1.81)
NTRgap_j	−1.18	−1.23*	−1.05	−1.31*	−0.90	−1.08	−1.61	−1.51	−1.43	−1.46**	0.71*	0.49
	(0.79)	(0.63)	(0.92)	(0.71)	(0.91)	(0.70)	(1.40)	(1.34)	(0.92)	(0.71)	(0.41)	(0.36)
Panel B. IV												
ΔFDI_{fj}	−17.96***	−14.45***	−18.41***	−12.28***	−22.50***	−16.44***	−15.16**	−13.53*	−18.65***	−11.34*	−3.42*	−4.34**
	(3.71)	(3.64)	(4.38)	(3.84)	(4.00)	(4.30)	(6.16)	(7.48)	(5.26)	(6.63)	(1.98)	(2.02)
NTRgap_j	−1.71*	−1.47**	−1.66	−1.52*	−1.66	−1.43*	−2.19	−1.85	−2.21*	−1.72**	0.44	0.31
	(0.94)	(0.72)	(1.12)	(0.80)	(1.03)	(0.77)	(1.68)	(1.51)	(1.15)	(0.84)	(0.38)	(0.26)
KP-*F*	139.32	190.80	139.32	190.80	139.32	190.80	124.11	181.29	81.46	134.73	121.75	179.55
Controls		✓		✓		✓		✓				
Mean dep. var.	8.69	8.69	−10.82	−10.82	0.52	0.52	35.91	35.91	6.33	6.33	62.76	62.76
# clusters	105	105	105	105	105	105	101	101	80	80	100	100
N	1017	1017	1017	1017	1017	1017	834	834	525	525	840	840

Notes: Standard errors clustered at the SIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.3). Estimation samples include US firms without international JV ties with China. The FDI shock ΔFDI_{fj} and the IV are defined in equations (3.4) and (3.5), respectively. In columns 1-2, 3-4, and 5-6, the dependent variables are US firms' changes in log sales, log employment, and inverse hyperbolic sine transformation of export values, respectively, between 1999-2012. The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. The even columns include 1996 US import penetration (overall imports, excluding US, China, India, Japan, and South Korea, relative to domestic absorption), 1993 production worker shares, 1990 computer investment shares, and 1-digit industry dummies. KP-*F* is the Kleibergen-Papp F-Statistics. All regression models are weighted by initial sales.

Table 5: China Shock and Indirect Negative Competition Effects. Sectoral Evidence

Dep.	ΔUS-CN import	ΔOC-CN import	ΔGross output	ΔEmp.	ΔPPI
	(1)	(2)	(3)	(4)	(5)
ΔFDI_j	8.30***	10.39***	−5.65**	−2.80**	−10.81***
	(1.97)	(2.71)	(2.53)	(1.37)	(3.63)
NTRgap_j	0.29	0.30	−1.50***	−1.01***	−1.73***
	(0.35)	(0.37)	(0.41)	(0.19)	(0.48)
KP-F	67.97	67.97	67.97	67.97	67.97
Mean dep. var.	136.68	146.98	14.37	−40.05	26.94
# clusters	130	130	130	130	130
N	383	383	383	383	383

Notes: Standard errors clustered at the CIC-3 digit levels are reported in parenthesis. *: $p < 0.1$; **: $p < 0.05$; ***: $p < 0.01$. This table reports the OLS and IV estimates of equation (3.6). ΔFDI_j is the FDI shock defined in equation (3.4) and the IV is defined in equation (3.5). The NTR gap is potential tariff increases on Chinese imports that would have occurred in the event of a failed annual renewal of China's NTR status prior to PNTR. KP-F is the Kleibergen-Papp F-Statistics.

FDI shock results in a 16.1 percentage point decline in sales growth. The result remains stable with the additional controls in column 2. The FDI shock also had negative effects on employment, capital, and export growth (cols. 3-8). The FDI shocks had negative impacts on US firms' innovation outcomes including R&D and patents (cols. 9-12). These results are also consistent with Autor et al. (2020) who found the negative impacts of the China shock on US firms' patents.

Sectoral evidence: China shock. We also show that FDI played a key role in driving the China shock, leading to the decline of US manufacturing. We run the following long-difference regression at the sector level for 1999-2012 using the same IV strategy:

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

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

Table 5 presents the results. The IV estimate indicates that US imports from China increased significantly in sectors with higher FDI shocks (col 1), with a one percentage point rise in the FDI shock leading to an 8.3 percentage point increase in US imports. Similarly, imports from China to other countries show the same pattern as US imports (col 2).[28] These sectors more exposed to FDI also faced significant declines in gross output and employment, aligning with our firm-level evidence (cols. 3-4), while declining price levels (col 5). The coefficients for the NTR gaps are significantly negative for

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

gross output, employment, and PPI. One standard deviation increase in the NTR gap decreased gross output by 23.4 (= 1.50×15.6) percentage points, whereas one standard deviation increase in the FDI shock decreased it by 12.9 (= 5.6×2.3) percentage points.

4. Theoretical Framework

In this section, we develop a dynamic general equilibrium model of FDI and innovation, capturing the three empirical facts documented in the previous section.

4.1 Setup

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

There are three types of firms: leaders, fringe firms, and JVs, with JVs formed through mutual agreements between leaders from both countries. We assume only Home firms establish JVs in Foreign, causing the set of operating firms in Foreign to vary across products and time, while Home's firm composition remains fixed. The firm sets for product j at time t are $\mathcal{I}_H = \{h, \tilde{h}\}$ for Home and $\mathcal{I}_{Fjt} = \{f, \tilde{f}, v\}$ for Foreign, where h and f are leaders, $\tilde{h}$ and $\tilde{f}$ are fringe firms, and v is a JV.

4.2 Household

A representative household in Home maximize Cobb-Douglas utility,

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

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

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

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

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

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

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

$$C^N_{Ht} = Z^N_{Ht} L^N_{Ht},$$

where Z^N_{Ht} is exogenous productivity of the non-tradable sector. With perfect competition, $P^N_{Ht} = \frac{w_{Ht}}{Z^N_{Ht}}$.

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

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

where y_{ijt} and y^*_{ijt} are the quantities of varieties produced by domestic and foreign firms for product j, with the superscript "$*$" indicating exported varieties. ψ_i is a demand shifter for each firm, where leaders in both countries and the JV share the same parameter value ($\psi = \psi_h = \psi_f = \psi_v$), while fringe firms share a different common value ($\tilde{\psi} = \psi_{\tilde{h}} = \psi_{\tilde{f}}$), which are normalized such that $\psi + \tilde{\psi} = 1$. The CES formulation allows for imperfect substitution between varieties within products, with the elasticity of substitution $\sigma \in (1, \infty)$ shaping the degree of substitutability. We neutralize love of variety by normalizing the sectoral output with the number of firms $\mathcal{I}_{jt} = |\mathcal{I}_H \bigcup \mathcal{I}_{Fjt}|$, because we do not want introducing a new variety by forming a JV to mechanically increase utility. The corresponding price index is

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

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

4.3 Firms

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

Leaders or JVs engage in Bertrand competition, charging variable markups over their marginal costs. Under the CES structure, their markups become a function of their market shares (Atkeson and

Burstein, 2008). Their prices in Home and Foreign markets are given by

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

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

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

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

Unlike the other types of firms, fringe firms charge monopolistically competitive constant markups.[29] Their prices and operating profits follow the same structure as those of leaders but are evaluated at zero market share.

Innovation. Leaders can improve productivity through successive innovations, while competitive fringe firms do not innovate. Innovations occur randomly at a Poisson rate x_{ijt} and have the following convex cost function:

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

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

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

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

Fringe firms do not innovate, and their productivity improves only through knowledge diffusion from domestic leaders, which will be discussed below.

Joint venture. A Foreign leader may collaborate with a Home leader to establish a JV in Foreign, which produces a new variety. The JV's production function is linear in labor, employing Foreign labor for production. The JV avoids trade costs when selling in Foreign but incurs trade costs when exporting to Home.

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

[29] Fringe firms can be interpreted as a continuum of atomistic, homogeneous firms, with their total mass normalized to one.

We assume that the JV maximizes its own profit rather than jointly optimizing total profits with its parent firms. This can be microfounded through the agency problem, where the manager of the JV maximizes only the profit of the JV it is managing, rather than the total profits in conjunction with its parent firms. A Home leader receives a κ share of the JV's total profits Π_{vjt}, while the Foreign leader retains the remaining $1-\kappa$. This assumption is based on the institutional details.

A Home leader chooses the probability of forming a JV, denoted by d_{Hjt}, with the following convex cost function:

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

where α_d governs the scale of the cost, and h^d_{Hjt} represents the labor employed for JV establishment. We assume that JV costs have the same curvature parameter as innovation costs due to the lack of information on the costs of setting up JVs.[30] h^d_{Hjt} captures expenses for training local managers or legal processing costs associated with setting up a new firm.

With a successful probability, the Home leader either pays or receives the endogenous one-time fee C_{jt} to or from the Foreign leader. The fee is determined by the Nash bargaining between them which will be detailed in the next subsection. This fee ensures mutual gains for both Home and Foreign leaders, with the surplus shared according to their respective bargaining powers.

Once a JV is established, it remains in operation until it exogenously dissolves with probability χ. While operating JVs with foreign partners, the leader can learn from advanced leaders in the foreign country, consistent with our first finding on the direct effects on Chinese parent firms. With probability ϕ, a lagged leader (either Home or Foreign) catches up to productivity of a more advanced leader.

Our formulation captures three key mechanisms of multinational production studied in the international trade literature. First, leaders have stronger incentives to establish a JV when Foreign has a larger market size (captured by a larger labor endowment), lower labor input costs, and higher iceberg costs between Foreign and Home. This aligns with the "proximity-concentration trade-off", a well-established concept explaining the gains of multinational production (e.g., Helpman et al., 2004). The one-time fee can be viewed as a generalization of fixed/sunk costs of FDI. The amounts of these sunk costs, and the party (Home or Foreign leaders) that bears these costs, are determined endogenously through Nash bargaining between Home and Foreign leaders, based on technology gaps.[31]

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

Third, our model also captures various positive spillovers associated with JVs. First, Home leaders' innovation improves Foreign JV's productivity, albeit subject to an iceberg productivity loss. This

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

[31] Since Home leaders establish JVs only when their additional profits exceed the one-time fee and due to the probabilistic nature of JV formation, our model accounts for the extensive margin of JVs observed in the data.

channel aligns with Bilir and Morales (2020), who study productivity spillovers from headquarters' R&D investments to foreign affiliates. Second, we allow for direct spillovers from Home leaders to Foreign leaders through JV formation, consistent with our first finding. Finally, because Foreign fringe firms can learn from Foreign leaders, these direct spillovers may also indirectly benefit Foreign fringe firms, capturing the indirect positive spillovers observed in our second finding.

4.4 Equilibrium

In this section, we define a Markov Perfect Equilibrium (MPE) of the model, where firms' strategies and JV formation decisions depend on payoff-relevant state variables.

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

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

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

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

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

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

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

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

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

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

δ^D and δ^F are probabilities of knowledge diffusion within and across countries. With probability $\delta^D > 0$, fringe firms attain the same level of productivity to domestic leaders. This type of domestic knowledge diffusion is consistent with our second finding and has been studied in the previous theoretical studies (Perla and Tonetti, 2014; König et al., 2022). δ^F is the probability that a lagged leader catches up to the productivity with an advanced foreign leader, while a Fringe firms' productivity levels remain fixed. δ^F captures knowledge diffusion across countries through channels other than JVs, such as international trade (see, e.g., Buera and Oberfield (2020) for a theory of knowledge diffusion through international trade).

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

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

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

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

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

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

Notably, the innovation rate is a function of technology gaps $\mathbf{m}$, as in Akcigit et al. (2023). The innovation rate is higher when the technology gap from either a domestic or foreign competitor is smaller since even a slight increase in productivity can significantly impact profits. Additionally, the innovation rate decreases with the diffusion rate because the option value of innovation declines when other firms can easily imitate new technologies.

Furthermore, the innovation rate also depends on the JV status. The effect of JVs on innovation is ambiguous. On one hand, US firms may have stronger incentives to innovate because productivity gains benefit not only their original establishments in the US but also their JVs in China. On the other hand, a higher diffusion rate reduces the innovation incentives of US firms, as the marginal returns to innovation diminish when technology is more easily diffused. In the quantitative section, we will demonstrate that innovation rates are indeed lower with JVs.

The optimal joint venture rate is expressed as follows:

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

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

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

where ξ is the bargaining power of Home leaders and Δ^{JV} denotes for changes in the value functions after forming a JV: $\Delta^{\mathrm{JV}}V_{it}(\mathbf{m}) = V_{it}(\mathbf{m};1) - V_{it}(\mathbf{m};0)$, $i \in \{h, \tilde{h}, f, \tilde{f}\}$. Note that $C_t(\mathbf{m})$ can be negative depending on the technology gap $\mathbf{m}$.

With Foreign leaders are more lagged behind with Home leaders (i.e., $m^F > 0$), Home leaders are more likely to receive adoption fees from Foreign leaders, as the latter gain significant learning opportunities and are willing to pay for forming JVs (i.e., $C_t(\mathbf{m}) \geq 0$). Conversely, when $m^F \leq 0$, Foreign leaders do not learn from Home leaders, but Home leaders still benefit from static market size gains from FDI. In this case, Home leaders pay adoption fees to Foreign leaders (i.e., $C_t(\mathbf{m}) < 0$).

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

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

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

Therefore, the optimal joint venture rate increases with the total surplus $(\Delta^{\mathrm{JV}} V_{Ht} + \Delta^{\mathrm{JV}} V_{Ft})$, given the bargaining power parameter ξ. Since the profits from establishing JV firm and the productivity gain from the diffusion increases with the productivity gap from the Foreign firms, the total surplus from JV also increases with the productivity gap ($|m^F|$).

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

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

Labor markets clear as

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

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

Equilibrium. We formally define a Markov perfect equilibrium and balanced growth path.

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

Definition 2. *A balanced growth path is the equilibrium defined in Definition 1 in which $\{w_{ct}, C_{ct}, A_{ct}\}$ grow at a constant rate g, and r_{ct} is constant over time.*

4.5 Taking Stock: Negative Competition Externality

The novel feature of our model is the negative competition externality associated with JVs. Knowledge diffusion from JVs to Foreign leaders and fringe firms enhance their global competitiveness, reducing profits for Home firms. Home leaders may overinvest in JVs as they do not internalize profit losses incurred by domestic fringe firms. Meanwhile, the static market access gains from JVs are exclusive to Home leaders, while they internalize their own future losses through bargaining fees.

In particular, knowledge diffusion probabilities (ϕ and δ^D) and leaders' demand shifters ψ are related to this negative externality. Higher diffusion probabilities increase spillovers from JVs, intensifying future competitive pressure on Home fringe firms. A higher demand shifter (ψ) implies that leaders hold a larger market share within products relative to fringe firms, thereby reducing the negative externality on fringe firms.

Beyond this, our model features other common market failures, typical of step-by-step innovation frameworks. Innovation by leaders generates knowledge diffusion to other firms, leading to a classic positive externality and underinvestment in innovation. Additionally, oligopolistic market power causes firms to produce below socially optimal levels, creating a standard distortion from market concentration.

5. Taking the Model to the Data

Home and Foreign correspond to the US and China. We solve the transition of the model starting from the initial condition in the year 1997, until it converges to the balanced growth path. We assume that the initial productivity gaps between Home and Foreign leaders follows distribution $N(\mathcal{D}, 1)$.[32] Greater $\mathcal{D} > 0$ indicates that Home firms' productivity is initially higher than Foreign firms. Although some sectors start with equal initial productivity levels, they diverge over time due to stochastic evolution driven by innovation and diffusion.

We also allow for time-varying import tariffs in the US and China, denoted t_t^{US} and t_t^{CN}, which applies to all products while assuming agents have perfect foresight on the path of these tariffs. JVs are also subject to the US import tariffs when exporting to the US.

With these additional elements, we calibrate total 21 parameters in three steps. First, we take 8 parameters directly from the data, externally calibrate 4 parameters from the literature, and jointly estimate 9 parameters using the simulated method of moments (SMM). Given an initial guess for the jointly estimated parameters, we solve for the model's transitions. Along the transition path, we compute the model moments and calculate their distance from the data counterparts. We minimize this distance by estimating the parameters.

We take the 8 parameters $\{L_H, L_F, \beta, \chi, t_t^H, t_t^F, \kappa, \xi\}$ directly from the data. The Home labor is

[32] Having a distribution instead of a single point allows us to assign non-integer values to $\mathcal{D}$, enabling us to implement the simulated method of moments on $\mathcal{D}$.

Table 6: Estimation Results

Parameter	Value	Description	Source / Main target
Directly from data			
L_F/L_H	2.83	Labor supply of China relative to US	Human-capital adj. pop. (Lee and Lee, 2016)
β	0.40	Tradable consumption share	1997 US Benchmark IO table
χ	0.08	JV exit rate	Avg. exit rate in CN (Chen et al., 2023a)
t_t^H, t_t^F		US/CN import tariff rates	Avg. import tariff rates
κ	0.54	US JV profit share	Avg. equity share of MNE
ξ	0.54	US JV fee bargaining power	Avg. equity share of MNE
Externally calibrated			
ρ	0.03	Time preference	Literature
σ	4	Elast. of subst.	Broda and Weinstein (2006)
γ	2	Innovation cost/JV cost curvature	Acemoglu et al. (2018)
τ^x	2.85	Iceberg trade cost	Bai et al. (2024)
Internally calibrated by SMM			
α_{Hr}	0.61	US R&D cost scale parameter	R&D / GDP in the US
α_{Fr}	0.82	CN R&D cost scale parameter	Long-run avg. gap= 0
α_{Hd}	1.54	US JV scale parameter	Avg. JV sales shares
λ	1.09	Step size	TFP growth rate in the US
$\mathcal{D}$	15.5	Initial technology gap	1999 mfg. value-added / emp. US/CN ratio
ψ	0.25	Leader & JV demand shifter	Mfg. US Compustat firm sales / gross output
ϕ	0.17	Prob. of direct knowl. diffusion	Direct effect on Chinese parents, Fig. 1
τ^z	1.76	JV iceberg technology cost	Sectoral regression results in US, Table 4
$\delta = \delta^D = \delta^F$	0.024	Prob. of exo. knowl. diffusion within/across cty	Sectoral regression results in China, Table 2

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

normalized to $L_H = 1$, while Foreign labor is set to $L_F = 2.83$, based on the human capital-adjusted population in China relative to the US (Lee and Lee, 2016). The consumption share of tradable-sectors β is set to 0.4 based on the 1997 US Benchmark input-output table. The exit rate of JVs χ is set to 0.08, based on the average exit rate of Chinese firms reported by Chen et al. (2023a). We directly take t_t^H and t_t^F from the data as the import-weighted average tariffs in manufacturing sectors.

The JV profit share κ is set to 0.54 based on the average equity share of MNEs in JV firms calculated from Orbis. This is based on the institutional details which state that each parent firm splits JV profits based on their equity shares. The bargaining power of US firms in JV fees is set to $\xi = 0.54$.

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

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

$$\min_{\boldsymbol{\Theta}} \sum_{m=1}^{9} \left(\frac{M_m^D - M_m(\boldsymbol{\Theta})}{\frac{1}{2}(M_m^D + M_m(\boldsymbol{\Theta}))} \right)^2 .$$

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

The R&D cost scale parameter for the US α_{Hr} is calibrated to match the average ratio of R&D expenditures to sales for manufacturing firms in Compustat, 1999–2013. α_{Fr} is calibrated to match Home and Foreign to have the same average productivity level in the steady state.[33] The JV cost scale parameter α_{Hd} is estimated to match the sales share of JVs in China during the sample period. Because the step size parameter λ increases with the targeted long-run growth rate, λ is calibrated to match the long-run TFP growth rate of the US of 0.6% for 2013–2013, obtained from FRED data from 2015 to 2019. The initial technology gap $\mathcal{D}$ is calibrated to match the initial value-added-per-employee ratio between the US and China in 1999, which was around 4.6.[34]

The demand shifter ψ is calibrated to match the overall share of US Compustat firm sales relative to total US gross manufacturing output, which is around 0.28 from 1999 to 2013 (Brault and Khan, 2024).

The probability of direct knowledge diffusion from US MNE to China leader ϕ is pinned down by our first fact. We obtain the average of the post-event study coefficients using the pooled diff-in-diff specification.[35] Then, we run the same specification using model-generated data, comparing leaders with JV and fringe firms within products, and target this coefficient.

The probability of indirect knowledge diffusion between domestic firms δ^D and JV iceberg technology cost τ^z are pinned down by the second and third findings, respectively. δ^D is directly related to the second fact of indirect positive spillovers, as this parameter governs the degree of knowledge diffusion across domestic firms. Because τ^z is associated with JVs' productivity losses, it is tied to the negative competition effects on US fringe firms, with higher values implying weaker competition. In the model, we simulate 100,000 sectors and construct the JV shock as in equation (3.4). Then, we run the same regression in equation (3.3) using fringe firms in the US and China and fit the OLS estimates in column 1 of Tables 2 and 5, respectively. This restriction of samples to fringe firms in the model is consistent with the sample restriction in the sectoral regression, where we excluded firms that ever engaged in JV investment. The detailed process is outlined in Appendix C.1.

Table 6 summarizes the estimation results, along with the sources and main targets for SMM. We obtain a value of $\mathcal{D} = 15.5$, implying that the productivity of Home firms is 4.3 times larger than that of Foreign firms on average. ϕ is estimated to be 0.162 while $\delta^F = 0.024$. This implies that having JV increases the probability of diffusion from 2.4% to 18.6%. $\tau^z = 1.755$ suggests that the effective productivity decreases by 75.5% in the JV, compared with the original US firms. Table 7 presents the moments from the model and the data, showing that the model closely aligns with the data.

[33] By targeting this ratio, we obtain $\alpha_{Fr} > \alpha_{Hr}$. This is because China has a larger labor endowment, so when $\alpha_{Hr} = \alpha_{Fr}$, Foreign has higher average productivity levels than Home in the balanced growth path.

[34] Manufacturing value-added data is sourced from the World Bank. US employment data comes from FRED, while Chinese employment data is obtained from the *China Labour Statistical Yearbook*, 2003.

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

Table 7: Target Moments in the Model and the Data

Moment	Model	Data
Sectoral regression results in US	−0.124	−0.113
Sectoral regression results in China	0.084	0.090
Direct effect on Chinese parent firms	0.197	0.200
Average TFP growth rate in US	0.057	0.059
Average R&D / sales in Compustat, manufacturing firms	0.066	0.065
Sales share of joint venture firms	0.108	0.110
Value added per emp. in mfg. in US / CN in 1999	4.800	4.545
Leader firms' sales share	0.283	0.280
Average productivity ratio in the long run	1.004	1.000

Notes. This table reports targeted moments of the model and data counterparts.

6. Quantitative Exercises

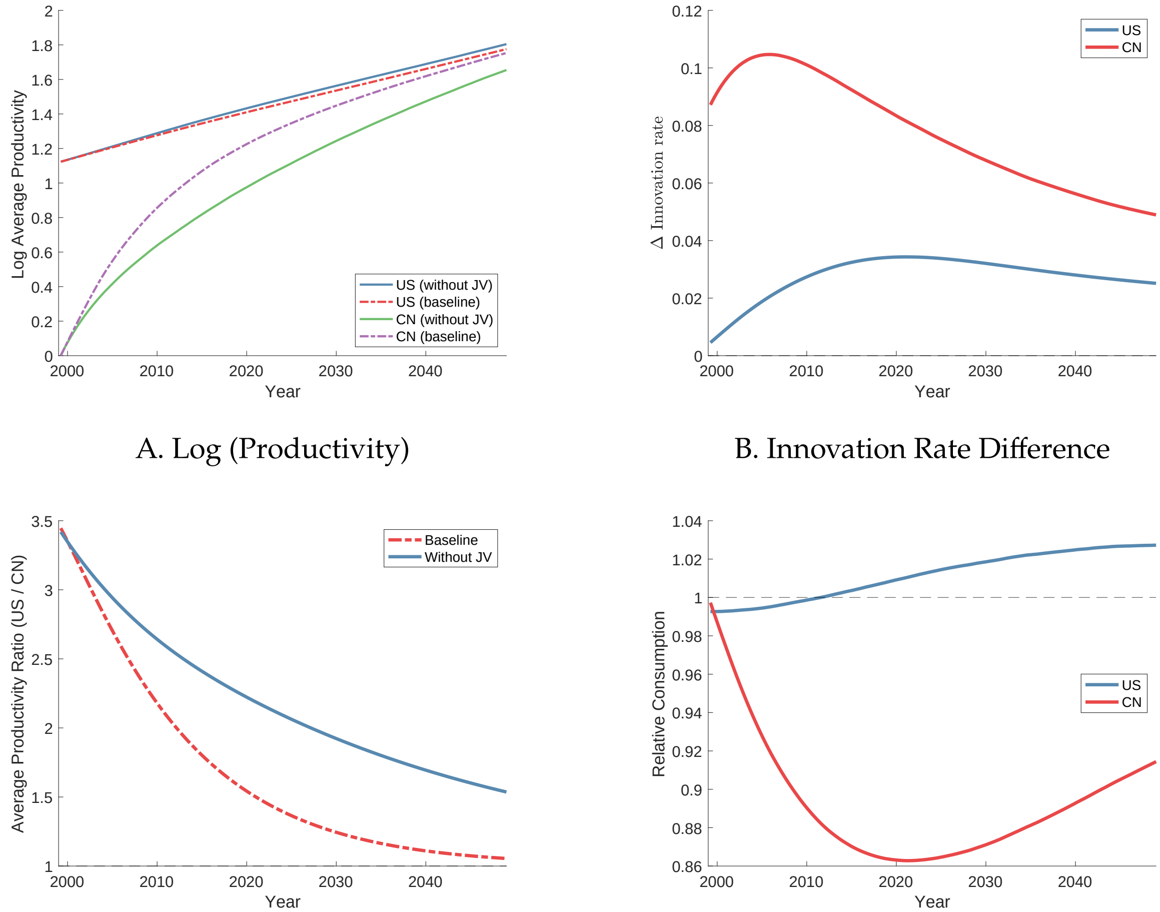
6.1 Did US Multinationals Transfer Too Much Technology?

In this section, we examine whether the US transferred too much technology to China through JVs in terms of US welfare. Specifically, we consider a counterfactual scenario in which the US government shuts down JV investment since 1999, and compare its welfare to the baseline scenario with JVs. Specifically, all existing JV firms exit and the firms are not allowed to establish JV anymore in the counterfactual. We assume that firms have perfect foresight about this policy change.

Panel A of Figure 3 compares the average productivity of leader firms in the baseline scenario with the counterfactual, for both the US and China. In the counterfactual, Chinese firms' productivity becomes lower after a few years due to reduced knowledge diffusion from joint ventures (JVs), which slows their productivity growth. Conversely, US firms experience a slight increase in productivity in the counterfactual. This is because US firms' innovation incentives respond to JV status—when more diffusion occurs through JVs, the marginal benefit of innovation diminishes, reducing the incentive to innovate (Aghion et al., 2001). Panel B illustrates the difference in innovation rates of US and Chinese firms between the counterfactual and the baseline, confirming that innovation rates are higher for both countries in the absence of JVs. Combined with the decreased Chinese firms' productivity, this leads to a wider productivity gap between US and Chinese firms in the counterfactual, as shown in Panel C of Figure 3.

Panel D of Figure 3 plot the relative consumption paths of the US and China when shutting down JVs compared to the baseline scenario. Initially, shutting JVs decreases US welfare because it loses profits from JVs. However, as China becomes less productive due to less knowledge diffusion from JVs, US firms become more competitive in the global market, which increases consumption roughly 11 years after shutting down JVs. In contrast, the reduced knowledge diffusion slows Chinese firms'

Figure 3: Baseline vs. Shutting Down JV



A. Log (Productivity)

B. Innovation Rate Difference

C. Productivity Ratio (US / CN)

D. Relative Consumption

Notes. Thie figure presents the results in the counterfactual where JVs are shut down, compared to the baseline scenario. Panel A plots log of average productivity of leader firms in US and China, under both the baseline and counterfactual scenarios. Panel B shows the difference in average innovation rates between the baseline and the counterfactual for both the US and China. Panel C plots the ratio of average productivity between US and Chinese firms for both scenarios. Lastly, Panel D presents the relative consumption paths of the US and China when JVs are shut down, compared to the baseline scenario with JVs.

productivity growth relative to the baseline, which decreases the relative consumption of China. However, after approximately 25 years, relative consumption begins to rise again as the productivity gap narrows and the role of diffusion diminishes for China. Appendix Figure C1 plots the level of consumption in the counterfactual along with the baseline.

To quantify the entire welfare effects, we compute the consumption-equivalent change of welfare, Ψ as below:

$$\int_{t=0}^{T} \exp(-\rho t) \log(C_{Ht}) dt = \int_{t=0}^{T} \exp(-\rho t) \log\Big(\hat{C}_{Ht}(1+\Psi)\Big) dt\,, \tag{6.1}$$

Table 8: Baseline vs. Shutting Down JVs. Welfare Effects

	US	China
Δ Welfare (%)	1.01	−9.11

Notes. This table presents the welfare effects for the US and China when JVs are shut down, compared to the baseline scenario with JVs. The welfare is in consumption equivalent unit from Equation (6.1).

Table 9: Baseline vs. Shutting Down JVs. Real Profits and Labor Income

	Baseline	Without JV	Changes
Profits of leaders	0.048	0.037	−22.00%
Profits of fringe firms	0.063	0.067	6.21%
Labor income	0.888	0.906	2.01%
Total real income	1	1.011	1.13%

Notes. This table presents the net present value of profits of US firms and labor income when JVs are shut down, compared to the baseline scenario with JVs. The profits of leader firms include both the operating profits of US leader firms and a share of the profits from JV firms. They are normalized by the total real income in the baseline.

Table 8 reports the results. When shutting down JVs, the US welfare improves by 1.01% compared to the baseline scenario, while China's welfare declines by 9.11%.

The effects of shutting down JVs vary across firms and labor. Table 9 compares the net present value of real profits of leader and fringe firms, as well as labor income, between the baseline and the counterfactual.[36] For leader firms, we aggregate their operating profits with a share of profits from JV firms. When JVs are shut down, leader firms experience a significant decline in profits, while fringe firms see a slight increase. Additionally, labor income rises in the counterfactual due to stronger labor demand in the US without JVs. Since labor income constitutes a large share of total household income, the net present value of total household income increases by 1.13% in the counterfactual.

6.2 Multilateral Bargaining: Coordinating JV

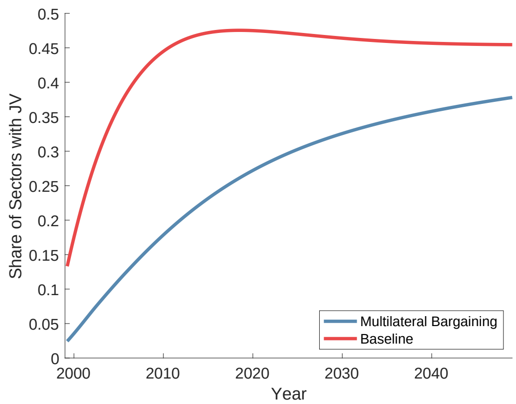
In the theory section, we discussed how the negative externality could lead to overinvestment in JVs by US leaders. In this subsection, we examine how JV investment would change if the externality were corrected and analyze its welfare implications.

To correct this externality, we consider a scenario in which US leaders compensate US fringe firms for their loses from JVs.[37] Specifically, we introduce an additional bargaining problem between US

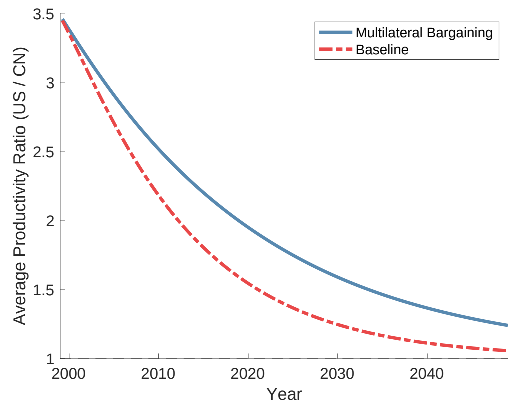
[36] We use $\rho = 0.03$ as the discount rate.

[37] An alternative approach is to formulate a social planner's problem and solve for the optimal JV levels across different technology gaps and time periods. However, this presents two key challenges. First, the step-by-step growth model features multiple market failures, such as underinvestment in innovation due to positive spillovers and inefficiencies from oligopolistic competition. The social planner's solution would address all these failures, making it difficult to isolate the effects of the negative competition externality. Second, the problem is computationally burdensome, as the solution is not

Figure 4: Baseline vs. Multilateral Bargaining Case



A. JV rate



B. Productivity Ratio (US/CN)

leaders and fringe firms. Unlike the baseline setup, a JV can only be established if US fringe firms also agree to its formation. We solve for this two bargaining problems jointly using the concept of Nash-in-Nash assuming that US leaders have full bargaining power in this case, we can express the modified bargaining outcomes as:

$$C = (1-\xi)\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \xi \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}), \qquad C^E = -\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}), \tag{6.2}$$

where C^E is the fee paid by US leaders to US fringe firms. Under this new bargaining structure, unlike the baseline setup where US leaders only internalize their own profits, US leaders now internalize both their own profits and those of US fringe firms. This can be shown from the fact that the sum of value changes $\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})$ enters the bargaining fee in equation (6.2), whereas in the baseline case, only $\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m})$ entered in equation (4.10). Additionally, US leaders to compensate fringe firms exactly by their losses from JV, as shown by $C^E = -\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})$. Because of this bargaining fees, US fringe firms do not incur profit losses from JVs.

Figure 4 compares the scenario with multilateral bargaining to the baseline. Panel A plots the share of sectors with JVs, showing that the JV share is lower under multilateral bargaining. This occurs because US leader firms must compensate fringe firms to establish JVs, making the process more costly. Consequently, fewer JVs are formed, leading to less diffusion from the US to China. Panel B presents the ratio of productivity between the average US and Chinese firms. The results indicate that the productivity gap is indeed larger in the multilateral bargaining case, suggesting that the reduced knowledge diffusion limits China's productivity growth.

analytically tractable and requires numerical methods, which become highly challenging due to the large state space and complex strategic interactions between firms within and across countries. These difficulties make it harder to implement the social planner's approach while focusing specifically on the negative competition externality.

Table 10: Welfare Effects of Shutting Down JVs under Multilateral Bargaining

Δ Welfare (%)	US	China
Multilateral Bargaining	1.04	−5.00
Multilateral bargaining + shutting down JVs	0.95	−9.51

Notes. The first row of this table presents the welfare effects for the US and China when requiring multilateral bargaining, in which leader firms compensate fringe firms for their losses when establishing JVs. The second row presents the welfare results when the government shuts down JVs under multilateral bargaining scenario. The welfare is in consumption equivalent unit from Equation (6.1), compared with the baseline case.

Table 10 presents the welfare results under the multilateral bargaining scenario. In this setting, consumption-equivalent welfare in the US increases by 1.04%, exceeding the welfare gain observed in the counterfactual where all JVs are shut down. Conversely, China's welfare decreases by 5.0%, suggesting that correcting externalities in the US can come at the expense of Chinese welfare but this loss is smaller than the baseline case.

The second row of the table reports welfare outcomes under a counterfactual scenario in which all JVs are shut down under multilateral bargaining. Compared to the first row, welfare declines in both the US and China. This result arises because multilateral bargaining aligns JV investments more closely with the optimal level; thus, restricting JVs introduces distortions and ultimately reduces overall welfare.

7. Conclusion

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

While we only considered a complete ban of joint ventures, in future research, one could investigate the welfare effects of other, more nuanced policies, such as targeted restrictions on technology transfers in specific sectors (so-called small yard, high fence), stricter intellectual property protection enforcement, or policies aimed at internalizing the negative externalities of joint venture formation. More importantly, our benchmark policy experiment assumed no response from the Chinese government. Developing a model in which the two countries' governments strategically interact through various policies will be an important next step, especially given China's active industrial policy, including the quid-pro-quo policy.

Furthermore, since tariffs will affect the negative competition effects from knowledge spillovers to

Chinese firms, one compelling avenue for future research is to explore how optimal tariffs and joint venture policies will interact—a direction we have taken in other ongoing work.

On the empirics side, our novel results on the direct and indirect effects of joint ventures on Chinese and US firms could be further refined to better understand the role of firm heterogeneity. For instance, how do the characteristics of different US leader firms (e.g., size, R&D intensity) influence their joint venture decisions and the extent of technology leakage? Similarly, how do the absorptive capacities of different Chinese firms affect their ability to benefit from spillovers? In addition, future research could explore alternative measures and methodologies to better quantify the direct and indirect effects of technology transfer through joint ventures.

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ONLINE APPENDIX

A. Appendix: Empirics

A.1 Concordance

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

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

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

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

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

where $\mathcal{J}_{ht}$ is a set of FDI affiliates with CIC h code in year t. For the regression models in Tables (4) and (5), we use the FDI shock defined at the 4-digit SIC codes.

Third, for the FDI shock used for the regression model in Table 2, we weight the SIC 4-digit level FDI shock using the mapping and the weights constructed in the first step:

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

where ω^h_j is a weight of SIC j assigned for CIC h.

A.2 Additional Figures and Tables

Table A1: Balance of Matched Sample. Direct Effects of Joint-Venture Formation on Chinese Partner Firms

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

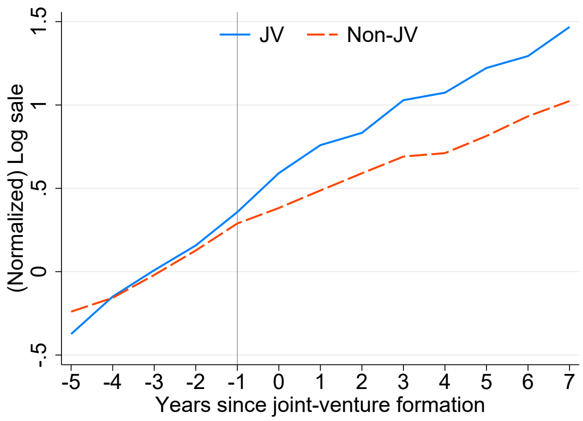
Notes. This table presents descriptive statistics for treated and control firms from five to one years before the event. Column 9 reports t-statistics for the mean differences between winners and losers, while Column 10 provides the corresponding p-values (in brackets), computed using standard errors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

Table A2: Balance Test. Direct Effects of Joint-Venture Formation on Chinese Partner Firms

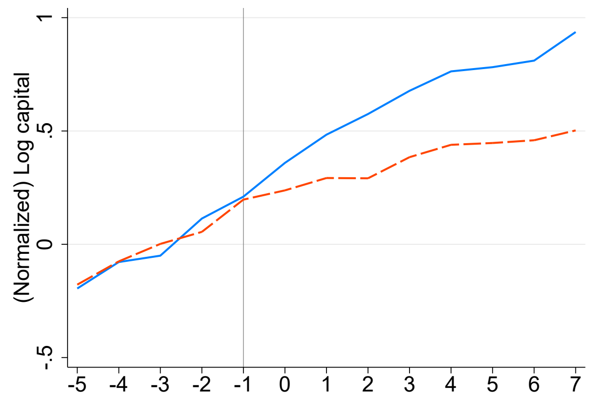
Dep. var.	Dummies of JV status										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Log sale	−0.003										
	(0.005)										
Log emp		−0.003									
		(0.007)									
Log sales per emp			−0.001								
			(0.009)								
Log capital				0.002							
				(0.004)							
Log capital per emp			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

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

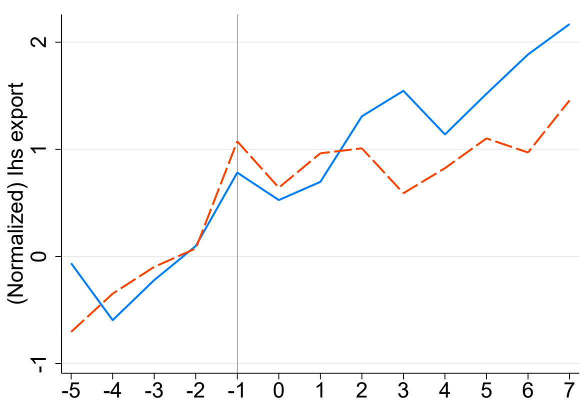
Figure A1: Raw Plots. Direct Effects of Joint-Venture Formation on Chinese Partner Firms



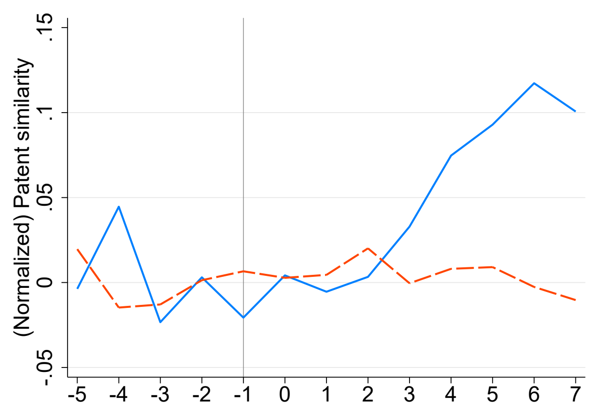
A. Log sale



B. Log capital



C. Ihs export



D. Technological proximity

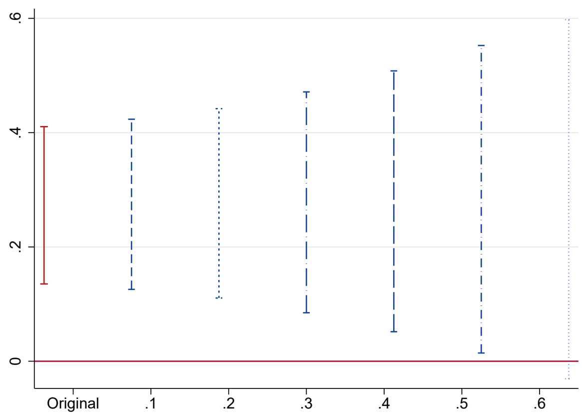
Notes. The figure presents the mean trends of log sales, log capital, the inverse hyperbolic sine transformation of exports, and technological proximity (measured by patents) for treated and control groups. The treated group is represented by the blue solid line, while the control group is shown with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

Table A3: Direct Effects of Joint-Venture Formation on Chinese Partner Firms

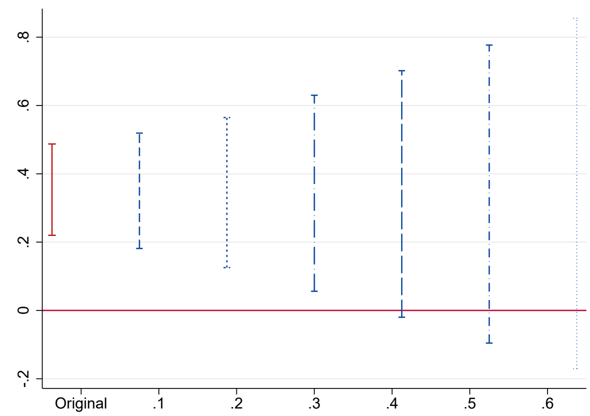
	Baseline outcomes				Alternative outcomes			
Dep. var.	Log sale	Log capital	Ihs export	Technological proximity	Log emp.	Dum. export	Ihs patent stock	Ihts annual patent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
5 years before	−0.03	0.02	0.78	0.03	−0.01	0.07	−0.12	−0.13
	(0.10)	(0.11)	(0.77)	(0.06)	(0.12)	(0.05)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

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

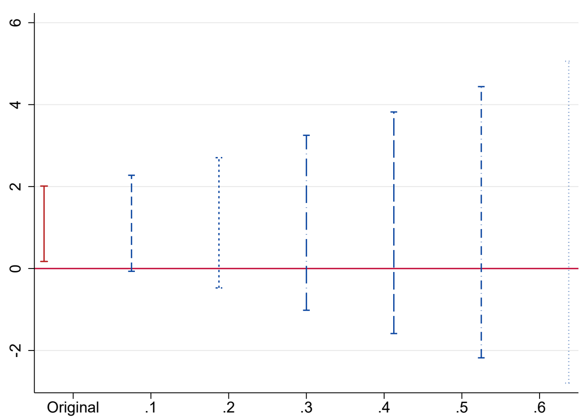
Figure A2: Robustness. Sensitivity to Violations of the Parallel Trend Assumption. Direct Effects of Joint-Venture Formation on Chinese Partner Firms



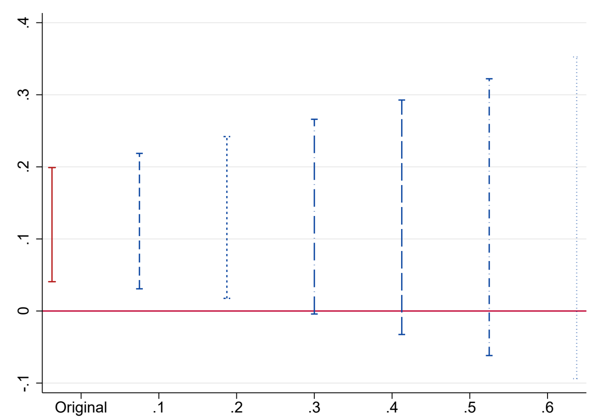
A. Log sales



B. Log capital



C. Ihs export



D. Tech. proximity

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

Table A4: Robustness. Alternative Number of Matches and Depreciation Rates for Patent Stock. Direct Effects of Joint-Venture Formation on Chinese Partner Firms

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

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

Table A5: Firm-Level Pre-trend. Correlations between the IV and Pre-1999 Firm Size Growth

	US firms DHS growth, 1993-1998			
Dep. var.	ΔSale (1)	ΔEmp. (2)	ΔCapital (3)	ΔExport (4)
IV_j	-2.78	-3.77	17.83	-15.05
	(17.83)	(21.53)	(13.10)	(35.21)
Mean dep. var.	13.43	-1.23	16.27	67.39
# Clusters	102	102	102	94
N	723	723	723	565

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

B. Appendix: Theory

B.1 Additional Expressions

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

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

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

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

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

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

A Home leader's value function with JV is

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

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

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

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

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

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

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

B.2 Nash-in-Nash Bargaining

We adopt the solution concept of Horn and Wolinsky (1988), known as the "Nash-in-Nash" solution, where each negotiating pair maximizes its Nash product, taking the actions of other pairs as given.

$$\begin{aligned}
C_t(\mathbf{m}) &= \underset{C}{\operatorname{argmax}} \left\{ \left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi} \times \left(\Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C\right)^{1-\xi} \right\} \\
&\text{s.t.} \quad \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) + C \geq 0 \\
&= (1-\xi)\left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C^E\right) - \xi \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m})
\end{aligned} \tag{B.8}$$

$$\begin{aligned}
C_t^E(\mathbf{m}) &= \underset{C}{\operatorname{argmax}} \left\{ \left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E\right)^{\xi^E} \times \left(\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E\right)^{1-\xi^E} \right\} \\
&\text{s.t.} \quad \Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C - C^E \geq 0, \qquad \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}) + C^E \geq 0 \\
&= (1-\xi^E)\left(\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) - C\right) - \xi^E \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})
\end{aligned} \tag{B.9}$$

Combining equations (B.8) and (B.9), we obtain

$$C = \frac{\xi^E(1-\xi)}{\xi^E(1-\xi)+\xi}\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m})\right\} - \frac{\xi}{\xi^E(1-\xi)+\xi}\Delta^{\mathrm{JV}} V_{ft}(\mathbf{m}) \tag{B.10}$$

$$C^E = \frac{\xi(1-\xi^E)}{\xi(1-\xi^E)+\xi^E}\left\{\Delta^{\mathrm{JV}} V_{ht}(\mathbf{m}) + \Delta^{\mathrm{JV}} V_{ft}(\mathbf{m})\right\} - \frac{\xi^E}{\xi(1-\xi^E)+\xi^E}\Delta^{\mathrm{JV}} V_{\tilde{h}t}(\mathbf{m}). \tag{B.11}$$

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

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

C. Appendix: Quantitative Exercise

C.1 Sectoral Regression in the Model

To estimate the model, we replicate the sector-level regressions in Section 3. Specifically, we simulate 100,000 products in the model, which are initially homogeneous. We assume that each product accounts for each sector. However, since innovation and diffusion are stochastic, sectors become heterogeneous over time in terms of their productivity gap relative to other firms. We then estimate Equations (3.3) and (3.6), with two key differences.

First, the model does not include additional control variables. Instead, we incorporate fixed effects for the productivity gap in 1999, which is equivalent to controlling for the initial sales of firms. Second, rather than using ΔFDI_{fj} as in the empirical analysis, we use the average sales share of JV firms in the model from 1999 to 2012. In our framework, JVs exit with an exogenous probability, meaning that the last period's JV sales share is not necessarily informative. For example, a sector initially without a JV firm may have had one from 2000 to 2011 but lost it due to exit in 2012. Despite this exit, Chinese firms in that sector may have already benefited from knowledge diffusion, increasing their market share in the US. In this case, ΔJV_{fj} could be negative, even though the sector was significantly influenced by JVs over time. To account for this, we use the average sales share of JV firms as the main independent variable. All other dependent variables remain consistent with the empirical analysis.

C.2 Decomposition Welfare Effects

$$\int_{t=0}^{\infty} \exp(-\rho t) \log(C_{Ht}) dt = \int_{t=0}^{\infty} \exp(-\rho t) \log\Big(\hat{C}_{Ht}(1+\Psi)\Big) dt \,, \tag{C.1}$$

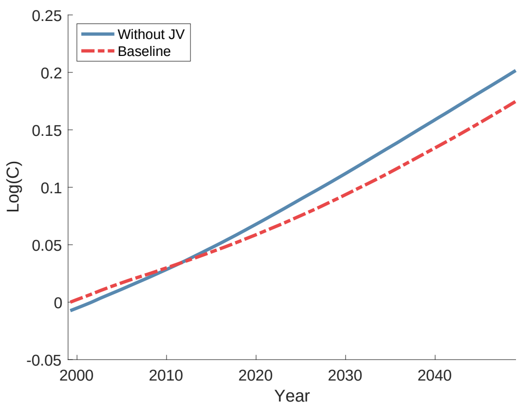
$$\log(1+\Psi) = \frac{1}{\int_{t=0}^{\infty} \exp(-\rho t) \mathrm{d}t} \int_{t=0}^{\infty} \exp(-\rho t) \log\left(1 + \frac{C_{Ht} - \hat{C}_{Ht}}{\hat{C}_{Ht}}\right) \mathrm{d}t \tag{C.2}$$

Applying the log approximation $\log(1+x) \approx x$ to both sides,

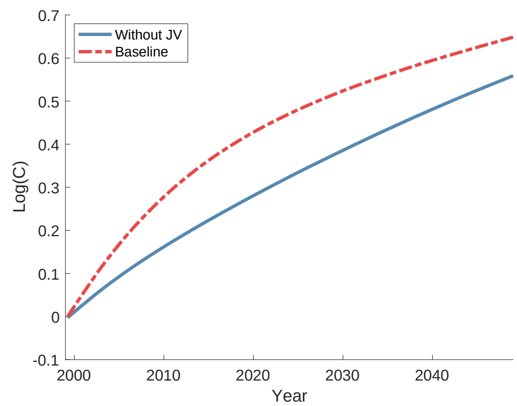
$$\Psi \approx \frac{1}{\int_{t=0}^{\infty} \exp(-\rho t) \mathrm{d}t} \int_{t=0}^{\infty} \exp(-\rho t) \frac{C_{Ht} - \hat{C}_{Ht}}{\hat{C}_{Ht}} \mathrm{d}t \tag{C.3}$$

C.3 Additional Figures and Tables

Figure C1: Baseline vs. Shutting Down JV. Path of Log(Consumption)



A. US



B. China

Notes. This figure presents log consumption of the US and China when shutting down JVs along with the baseline scenario with JVs.