How do Multinationals Impact China's Technology? The Role of Quid Pro Quo Policy and Technology Spillovers

Ma, Xiao and Zhang, Yiran

Peking University, Fudan University

24 May 2024

How do Multinationals Impact China's Technology? The Role of Quid Pro Quo Policy and Technology Spillovers*

Xiao Ma
Peking University

Yiran Zhang
Fudan University

May 24, 2024

Abstract

Multinationals play a crucial role in international knowledge diffusion. Using comprehensive patent data, we document: (1) multinational affiliates and their foreign parent firms comprise a significant portion of patents filed with China's patent office; and (2) there are subsequent transfers and spillovers of these technologies to domestic firms. Guided by this evidence, we develop a model of multinational production featuring cross-country idea flows, transfers, and spillovers. Quantitatively, we find that without multinational production and knowledge spillovers, the idea stock owned by China would drop by 27%. Furthermore, due to the externalities of multinationals through technology transfers and spillovers, subsidizing multinationals will at most increase real income by 8% in China.

Key Words: multinational activities; technology transfers; knowledge spillovers
JEL Codes: F23; O33

*Email: xiaomaecon@gmail.com; yiran_zhang@fudan.edu.cn. We thank David Atkin, Gordon Hanson, David Lagakos, Yuhei Miyauchi, Natalia Ramondo, Xiaodong Zhu, and seminar/conference participants at Peking University, Boston University, Renmin University, SUFE, and the 1st International Economics Joint Conference for their helpful comments. All potential errors are our own.

1 Introduction

A notable aspect of globalization is the escalating significance of multinational activities worldwide especially since the 2000s,[1] and many economists view this as a new "stylized" fact of economic development (Jones and Romer, 2010). A key feature of multinationals is that they frequently bring know-how across borders and thus facilitate international idea flows. A large body of research has already studied how multinational activities bring production technology to other nations (e.g., Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018) and how these technologies are transferred to or absorbed by domestic firms in host countries (e.g., Holmes, McGrattan and Prescott, 2015; Amiti et al., 2023). Most of these studies rely on production and trade data, however, relatively less effort has been directed to empirically and quantitatively evaluating the technology flows directly using technology data.

In this paper, we bridge this gap in the literature. Our analysis focuses on China, which has been a prominent recipient of FDI and serves as an ideal setting to study multinational activities.[2] Evaluating China's case is also particularly policy-relevant given the recent slump in China's FDI inflows (Barklie, 2023), particularly due to geopolitical issues and supply chain disruptions (Freeman and Baldwin, 2020; Grossman, Helpman and Lhuillier, 2023). Through analyzing comprehensive patent data from China, we present evidence regarding the technologies introduced to China through multinational activities, as well as the subsequent transfers and spillovers of these technologies to domestic firms. Guided by these empirical findings, we then develop a tractable framework of multinational activities featuring cross-country technology flows, transfers, and spillovers. Finally, we quantitatively evaluate the overall impact of multinational activities on China's technology stock.

We begin our analysis by assembling a comprehensive dataset of all multinational affiliates registered in China, with information on their ownership structure and patenting activities during 2000–2015. We document two novel facts. Firstly, we discover that multinational affiliates and their foreign parent firms comprise a significant portion of China's technologies. Between 2000 and 2015, multinational affiliates and their foreign parent firms accounted for 6% and 18% of all patent applications filed with China's patent office, respectively. More intriguingly, we observe that patents owned by multinational affiliates were mainly innovated within

[1]From 2000 to 2015, global foreign direct investments (FDI) surpassed 29 trillion dollars. Jones and Romer (2010) show that the ratio of World FDI to World GDP increased steeply in the 2000s.

[2]China accounted for 9% of global FDI inflows between 2000 and 2015.

China, whereas patents owned by foregn parent firms largely featured innovations made overseas and were predominantly related to advanced technologies (primarily smart phones and semiconductors), indicating substantial cross-border knowledge flows. We also provide suggestive evidence showing that technologies brought by parent firms were also integrated into the production processes of their affiliates.

Secondly, we document nonneglible technology transfers and spillovers from multinationals to domestic firms. Direct technology transfers (patent transactions and licenses) to domestic firms accounted for 4.2% of all patents brought by multinational affiliates and their foreign parent firms into China. Consistent with the recent evidence (Bai et al., 2020), we find that joint ventures held a large number of patents and potentially played a big role in transitioning multinationals' innovation into China's domestic firms. As for indirect technology spillovers, we follow the literature (Bloom, Schankerman and Van Reenen, 2013) to construct the spillover flows based on the number of patents brought into China and the similarity between multinational affiliates (their parent firms) and domestic firms in the technology space. We find that spillover flows had a positive impact on domestic firms' innovative activities. The positive effects remain when we take advantage of the relaxation of FDI regulations following China's WTO accession to lessen the endogeneity concern.

Guided by the two facts, we construct a model to quantify the impacts of multinational operations on China's technology. Our model is based on the classical Ricardian framework of trade and innovation developed by Eaton and Kortum (2001). In this framework, entrepreneurs in each nation determine their R&D investments, thereby augmenting the local technology stock. To incorporate cross-border idea flows, we extend this framework by allowing entrepreneurs to pay fixed costs for transferring ideas and establishing production facilities abroad, as similarly modelled by Arkolakis et al. (2018) in a Melitz-type model. Informed by our empirical findings, we further incorporate two features of these cross-border idea transfers. Firstly, we examine the potential influence of "Quid Pro Quo" policies in host countries, which may require technology transfers to domestic firms, potentially dampening incentives for idea dissemination. Secondly, recognizing the positive spillover effects of multinational firms on local entities, we incorporate knowledge spillovers into the production function of new technology. This allows us to quantify the extent to which knowledge brought by multinationals can diffuse and benefit domestic firms in host countries.

Through the lens of our model, we first show analytically that multinationals can exert both positive and negative effects on domestic innovation activities within host countries. On one hand, multinationals bring technologies and reduce the costs of accumulating new technology via spillover effects. On the other hand, multinational entry may escalate competition and thus reduce the benefits for domestic firms to engage in innovation activities. The overall impact of multinational entry on domestic innovation hinges upon the interplay between these opposing forces. Furthermore, we show that the gains in real income from multinational production can be decomposed into static and dynamic components. The static component captures changes in prices and profits, resembling the ACR formula in the presence of multinationals (Ramondo and Rodríguez-Clare, 2013). The dynamic component captures changes in R&D inputs and idea stock, as multinational entry alters domestic R&D and idea stock through a confluence of technology transfers, spillovers, and competitive pressures.

We calibrate our model to the manufacturing sector across 62 countries spanning the period from 2000 to 2015, using the data moments on production, trade, multinational activities, and innovation. The calibrated model effectively aligns with the targeted data moments. Notably, our model matches the proportion of multinationals' output within China's total output and the percentage of multinational patents granted in China relative to the total patents granted in the country each year.

Using the calibrated model, we quantify the impact of multinational activities on China's technology. To this end, we simulate a counterfactual scenario without multinationals' production and knowledge spillovers in China. We find that the idea stock owned by China would drop by 27.3% (China's GDP would decline by 13.7%) from the baseline equilibrium. This decline is primarily due to the absence of knowledge transfers via the Quid Pro Quo policy. Interestingly, in this scenario, the idea stock generated by Chinese domestic firms would increase by approximately 6.3%, suggesting that multinational entry has an overall negative net effect on domestic innovation (the negative effect of intensified competition outweighs the positive effect of increased knowledge spillovers). In line with these results, among the overall gains from multinational production, we find that the contribution of the dynamic component is more than 95%. This substantial dynamic gain stems from technology transfers that elevate China's idea stock, as well as knowledge spillovers that reduce the number of R&D workers needed to achieve the similar level of R&D output.

We also perform four sets of additional analyses. First, we find that without knowledge spillovers from multinationals, the idea stock generated by Chinese domestic firms would decrease by 10.6%, reaffirming the positive effects of multinationals on China's technology via knowledge spillovers. Second, we find that shutting down the Quid Pro Quo policy would increase China's GDP by 10.4%, while reducing China's idea stock by 37.3% due to the lack of technology transfers. Third, we find that if multinationals halve their intensity of using ideas to China, China's GDP is projected to drop by 11%, with the idea stock declining by 25.5%. There is a notable increase in GDP especially for neighboring Asian economies, primarily fueled by heightened exports and multinational operations. Finally, we find that as a result of positive externalities from multinationals' technology transfers and spillovers, subsidizing multinational production in China would be socially beneficial. At a subsidy rate of 20% for multinationals' production costs, China's real income (net of subsidy costs) increases by 8%, with an overall GDP increase of 11%.

Our paper is related to several stands of the literature. Our focus on knowledge transfers and spillovers connects us to a vast literature on knowledge diffusion across borders. Many studies have examined the effects of international knowledge diffusion (e.g., Coe and Helpman, 1995; Eaton and Kortum, 1999; Buera and Oberfield, 2020), as reviewed by Keller (2021). Among the mechanisms, foreign investment plays a crucial role (e.g., Aitken and Harrison, 1999; Konings, 2003; Javorcik, 2004; Keller and Yeaple, 2009; Alviarez, Cravino and Ramondo, 2023). While these prior studies mainly focused on the productivity impact of foreign firms' knowledge spillovers, we focus on their impact on innovative activities. Our assembly of rich patent data provides a clear measure of firms' innovative activities and facilitates the construction of knowledge spillovers based on the similarities of technologies in the technology space (Bloom, Schankerman and Van Reenen, 2013). This measure of knowledge spillovers also allows us to empirically disentangle the two opposite effects of multinational entry on domestic innovation—knowledge spillovers and intensified market competition—which are often confounded in most empirical studies on knowledge spillovers from foreign investment (see Amiti et al. (2023) for a review).

Our paper also contributes to the literature on foreign investment in China. China's fast growth in recent decades has offered many policy implications for developing economies. One key stimulus of China's growth is the surge in FDI inflows (Branstetter and Foley, 2010). While a plethora of studies have empirically examined the effects of foreign investment on trade and productivity of domestic firms in China (e.g., Liu, 2008; Manova, Wei and Zhang, 2015; Wang and Wang, 2015; Lu, Tao and Zhu, 2017; Jiang et al., 2024), fewer studies have quantitatively analyzed its impact (e.g., Brandt and Lim, 2019; Deng et al., 2023). Our paper is mostly related to Holmes, McGrattan and Prescott (2015), from which our paper differs in several aspects. Firstly, whereas they build on a neoclassical model augmented with technology capital and abstract from trade, we develop our framework based on a Ricardian model, which allows us to tractably consider both trade and multinational production in a unified framework.[3] Secondly, instead of calibrating the strength of technology transfers to match FDI flows as in their paper, we use patent data to directly measure transfers, following the literature that employs patents as a proxy of technology (e.g., Akcigit, Celik and Greenwood, 2016). Finally, we additionally show that multinationals can impact host countries' technology through knowledge spillovers to local firms.

By employing a quantitative framework, our paper also contributes to an extensive body of literature that utilizes quantitative models to examine trade, multinational production, and innovation. Our model builds upon the Ricardian framework proposed by Eaton and Kortum (2001), augmented by the incorporation of decisions regarding idea flows across borders to establish foreign production facilities ("multinational activities"). Several recent studies also explore the connection between multinational production and innovation (e.g., Arkolakis et al., 2018; Bilir and Morales, 2020; Fan, 2023). Our paper supplements theirs by emphasizing that multinationals can influence the technology of host countries through Quid Pro Quo policies and knowledge spillovers, aspects that have received limited attention in these studies.

Finally, this paper makes contact with studies on China's innovation from a macro perspective. Few macro-level studies explore the causes of China's innovation. Ding and Li (2015) provide a comprehensive summary of government R&D policies in China. Chen et al. (2021) show that China's reform of R&D tax incentives in 2008 changed firms' R&D behavior. König et al. (2022) evaluate the role of output wedges in shaping Chinese firms' R&D efficiency in a stationary equilibrium. Chen, Li and Zhu (2023) discusses the role of local governments' institutional changes in shaping China's innovation. This paper complements these studies by focusing on the role of foreign investment in driving Chinese firms' innovative activities.

This paper is structured as follows. Section 2 documents descriptive facts on technologies brought by multinational activities into China. Guided by the evidence, we develop a quantitative model in Section 3 and then calibrate the model in Section 4. We quantify the impact of multinational activities on China's innovation in Section 5. Finally, we conclude in Section 6.

[3] In terms of multinationals' location choices, a significant consideration arises with the proximity-concentration trade-off. This trade-off delineates the balance between attaining proximity to consumers and consolidating production for scale economies (Brainard, 1997). Our framework accommodates this trade-off by integrating both trade and multinational production within a unified framework.

2 Descriptive Facts

In this section, we leverage our data to shed light on two important aspects of multinational firms' impact on domestic innovation: their patenting activities and the subsequent transfers and spillovers of their technologies to domestic firms. We begin our analysis by first describing the data used in our study.

2.1 Data

Multinational Firms. We use China's Registration Information of Industrial and Commercial Enterprises in 2015, which covers all firms registered within China before 2015 with information on these registered firms' investors. We identify firms with at least 30% equity share belonging to foreign investors[4] as *multinational affiliates* and extract the name and nationality information of these firms' investors. In total, we identify 455,226 multinational affiliates that were registered in China up until 2015. On average, foreign owners hold 85% of equity in these multinational affiliates. We refer to foreign owners as *foreign parent firms* hereafter. Appendix Table A.1 documents that the majority of multinational affiliates in China originated from Hong Kong,[5] Taiwan, Japan, Korea, and the United States with each of these source regions accounting for over 5% of all multinational affiliates between 2000 and 2015.

In addition to the Registration Information of Industrial and Commercial Enterprises, we also obtain information on manufacturing firms' production from China's Annual Survey of Manufacturing (ASM) for the years 2000–2007. This dataset provides detailed financial information such as sales, employment, and capital stock, as well as 4-digit industry affiliation for all manufacturing firms above a certain threshold (roughly 600 thousand dollars).[6] By combining the ASM data with our dataset on multinational firms, we can investigate the impact of multinational firms on manufacturing innovation and production in China.

[4]To determine the foreign status of these firms' investors, we consider investors as foreign if they originated from regions outside mainland China. The rationale behind our decision to set the threshold at 30% is that in certain industries, foreign investors were restricted from owning more than a 50% equity share for a prolonged period. Our results are robust if we use thresholds of 0% or 50%.

[5]There is a concern regarding the legitimacy of some multinational affiliates originating from Hong Kong, as they might essentially be Chinese domestic firms that register in Hong Kong to take advantage of tax incentives. While identifying these "fake" multinationals poses empirical challenges, we find that our results remain robust even after excluding multinational affiliates from Hong Kong.

[6]Because the data covers all medium-size and large firms, it is informative about aggregate manufacturing sales. Brandt, Van Biesebroeck and Zhang (2012) find that below-scale firms only produced 9.9% of total industrial output in 2004.

Patent Data. We use Chinese patent application data assembled by the China National Intellectual Property Administration. It provides a comprehensive source of data that can be used to gain insights into the innovation activities of Chinese firms, covering detailed information on each patent, including the unique application number, application date, grant date, inventors, and International Patent Classification (IPC) code. We focus on all invention applications that were applied by firms between 2000–2015 and eventually granted,[7] which added up to 2,289,713 patents.

To gain a deeper understanding of technology transfers in China, we obtain comprehensive data on patent transactions and licenses. This data provides information on the transfer of patented technology from one firm to another through licensing agreements or outright sales. The data on patent transactions and licenses includes information such as the patent's transaction/licensing date, the patent's application number, and the names of the firms involved in each transaction or license. We follow Akcigit, Celik and Greenwood (2016) to exclude transactions and licenses between firms with similar names, avoiding technology transfers within company groups.

We link all patent data together using the patent's unique application number. We link the patent data with firm-level data using firms' names, after cleaning and standardizing firm names. The specifics regarding the datasets and the process of consolidating firm names are outlined in Appendix B.

2.2 Multinationals' Patenting Activities

Fact 1 *Multinational affiliates and their foreign parent firms account for a considerable portion of China's technologies. In particular, they bring advanced technologies to China from overseas.*

Figure 1 shows the yearly number of patents applied by multinational affiliates and their foreign parent firms to China's patent office from 2000 to 2015. In 2000, multinational affiliates applied for only around two hundred patents. However, following China's rapid increase in foreign investments especially due to WTO Accession in 2001 (Brandt et al., 2017) and the relaxation of regulations on foreign investments in 2002 (Lu, Tao and Zhu, 2017), multinational affiliates' patent applications began to increase rapidly. By 2015, multinational affiliates were applying for around 19 thousand patents annually in China. In comparison, foreign parent firms applied for a

[7] Our complete patent sample concludes in 2020; therefore, for a patent to be incorporated in our data set, it must have been granted before that year. Typically, it takes approximately three years for a patent to be granted following its application in China.

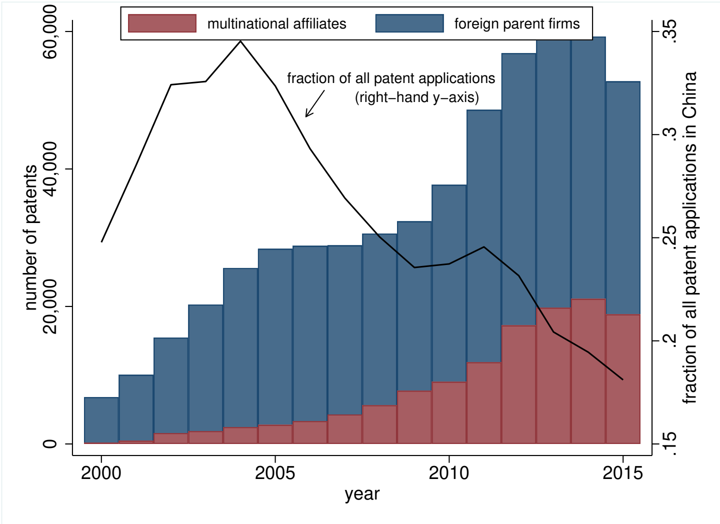


Figure 1: Number of Patents Applied by Multinational Affiliates and Foreign Parent Firms

higher number of patents in the early 2000s, with around 7 thousand patent applications annually, which increased to 34 thousand applications in 2015. The growth in the number of foreign parent firms' patent applications appeared to be less dramatic than that of affiliates' applications in the later years.

Table 1 provides the summary statistics of the patents filed with China's patent office between 2000–2015. Over the 2000–2015 period, multinational affiliates and their foreign parent firms applied for 128,234 and 413,790 patents, accounting for 5.6% and 18.1% of all patents applied to China's patent office. Thus, multinational affiliates and their foreign parent firms combined accounted for about a quarter of China's patent applications between 2000 and 2015. In Figure 1, the auxiliary y-axis displays the annual proportion of patent applications filed in China's patent office by multinational affiliates and foreign parent firms. This proportion experienced an increase in the early 2000s, but it began to decline after 2004, which could be attributed to the growing involvement of domestic Chinese firms in innovation (Wei, Xie and Zhang, 2017). Nevertheless, even in 2015, multinational affiliates and foreign parent firms still contributed to 18% of all patent applications in China. Despite that some of multinationals' technologies used in China may not be registered in China's patent office and captured by our data, the existing percentage already demonstrates a substantial contribution of multinationals to technologies available in China.

Our analysis so far highlights the importance of multinational affiliates and their foreign parent firms in China's patents. A natural concern is about the sources of their patents: if their patents mostly arose from innovation within China, their patenting activities would also utilize China's R&D resources and may crowd out domestic firms' innovation. To understand the origins of firms' patents, we use the information on the physical address of each patent. We find that 2% of multinational affiliates' patents have a foreign address, and that 88% of their foreign parent firms' patents have a foreign address, as shown by Table 1. This pattern is robust when we utilize information on the country of patents' priority rights (the first filing of an application): 3% of multinational affiliates' patents were first applied overseas, whereas 84% of parent firms' patents were first applied overseas. Figure 2a illustrates the top 10 source countries and regions of foreign parent firms' patents based on address, showing that their patents mostly came from Japan, South Korea, Germany, and the US. Overall, this pattern suggests that multinationals not only bring technology into China by themselves but also perform innovation in China through affiliates, consistent with the evidence for US multinationals in Bilir and Morales (2020).

To understand whether multinational affiliates and their foreign parent firms bring advanced technologies into China, we follow Webb et al. (2018) to apply text analysis to determine whether each patent belongs to 10 advanced technologies (e.g., software, smart phones, drones) based on patents' titles and abstracts. Figure 2b exhibits the share of high-tech patent applications by multinational affiliates, foreign parent firms, and domestic firms relative to their respective total patent applications from 2000 to 2015. We find that patents by multinational affiliates and foreign parent firms were overwhelmingly concentrated in smart phones and semiconductors. In particular, patents related to smart phones and semiconductors accounted for around 25% of all the patents brought by foreign parent firms into China in 2000–2015. In Appendix Figure A.1, we plot the time-series pattern of the shares of patents for the four major advanced technologies (smart phones, semiconductors, software, pharmaceuticals). For these technologies, the rise in multinational affiliates' and their foreign parent firms' patent applications started earlier than the rise in China's domestic patent applications, where the timing suggests a story of technology spillovers from multinational activities to Chinese domestic firms, as we will test in the next subsection.

Given that foreign parent firms' patents were mostly brought from overseas, one may wonder whether they were actually applied to China's patent office for royalty allowance and not directly used in production. To explore this, we provide suggestive

Table 1: Summary of Patents Applied to China's Patent Office between 2000–2015

	Amount	% Foreign Address	% Foreign Priority Rights
Multinational Affiliates:	128,234	1.48%	2.60%
Joint Ventures	43,932	1.19%	2.23%
Foreign Parent firms	413,790	88.05%	83.80%

Notes: Our computation is based on patents that were applied by firms between 2000 and 2015 and eventually granted before 2020.

evidence. Specifically, we perform the following regression:

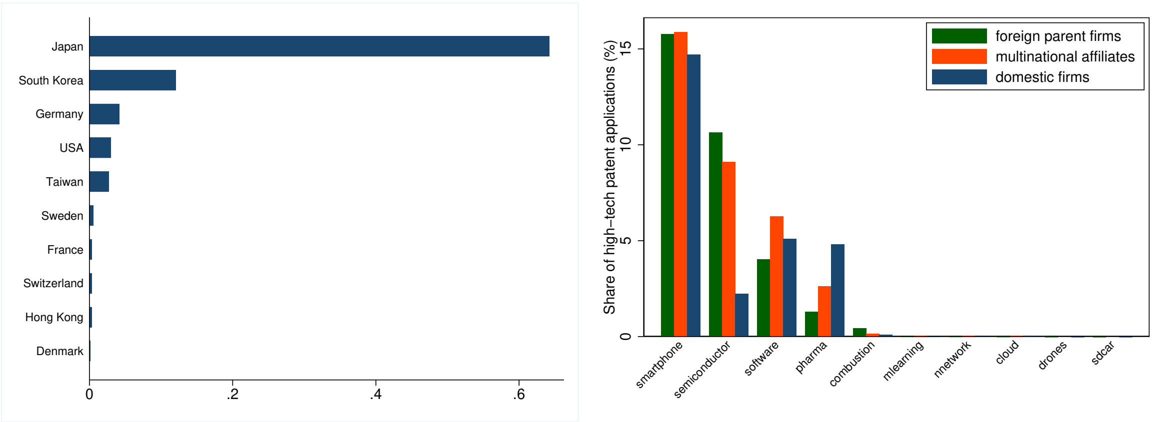
$$\log y_{it} = \beta_1 arcsinh(cumul\_patent_{it}) + \beta_2 arcsinh(cumul\_patent\_par_{it}) + \alpha \mathbf{X}_{it} + \mu_i + \gamma_{s(i),t} + \epsilon_{it}. \quad (1)$$

In our primary results, we use firm sales as the dependent variable y_{it}. $cumul\_patent_{it}$ represents the cumulative count of firm i's own patent applications to year t, while $cumul\_patent\_par_{it}$ indicates the cumulative count of patent applications by foreign parent firms of firm i up to year t. Due to the potential presence of zeros in $cumul\_patent_{it}$ and $cumul\_patent\_par_{it}$, logarithmic transformation is not feasible. Hence, we resort to employing the inverse hyperbolic sine (IHS) transformation for patent numbers.[8] In Appendix Table A.3, we show that the results are robust if we apply the log1plus transformation to patent numbers. $\mathbf{X}_{it}$ is the vector of firm-level controls, including capital, employment, and registration types (e.g., private or state-owned firms). We also control for firm fixed effects μ_i, which captures time-invariant firm characteristics (e.g., firm age), and industry-year fixed effects $\gamma_{s(i),t}$ to capture industry-specific time trends, where $s(i)$ corresponds to firm i's affiliated 4-digit industry. We combine patent and firm-level data to perform this regression for manufacturing firms in 2000–2007. Appendix Table A.2 presents the summary statistics for the data.[9]

Column (1) of Table 2 shows that the cumulative amount of patent applications has a positive association with firm sales for all firms, after controlling for firm and industry-year fixed effects. The results still hold when we include firm-level controls in Column (2). Columns (3)–(5) report the results for multinational affiliates under different specifications, where we include the cumulative amount of foreign parent firms' patent applications in Column (4) and incorporate firm-level controls in Column (5). We find that both the cumulative number of the firm's own patent applications and

[8] The IHS transformation of variable x is given by $arcsinh(x) = \log(x + \sqrt{x^2+1})$.

[9] Consistent with the multinational affiliates' productivity premium documented in the literature (e.g., Setzler and Tintelnot, 2021), we find that on average, multinational affiliates were larger and had higher sales per worker than domestic firms in China.



(a) By Region (Parent Firms' Patents)

(b) High-tech Types

Figure 2: Characteristics of Multinationals' Patents

that of its foreign parent firms' patent applications are positively associated with firm sales, and the coefficients are similar in magnitude. Appendix Table A.3 confirms the robustness of the results using TFP levels as the outcome variable.

Although the coefficients in Table 2 only reflect the correlation, we take these as supportive evidence that foreign parent firms' patents are actually directly used in their affiliates' production. This evidence is consistent with the broad multinational literature (e.g., Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018), which usually considers that multinational affiliates' production technology comes from their headquarters.

2.3 Technology Transfers and Spillovers

Fact 2 *There are direct technology transfers from multinational affiliates (and their foreign parent firms) to domestic firms. Joint ventures and knowledge spillovers from multinational activities may also play important roles in impacting domestic firms' technology levels.*

Direct Technology Transfers. We first use the patent transaction and license data, which records the direct technology transfers from multinational affiliates (and their foreign parent firms) to domestic firms. As shown by Table 3, 10.45% of patents applied by multinational affiliates between 2000 and 2015 were sold to domestic firms, and 2.26% of patents applied by their foreign parent firms between 2000 and 2015 were sold to domestic firms.[10] Licensing occurs much less frequently: only 0.42%

[10]We limit the timeframe for patent transactions to be prior to 2021, accommodating potential delays in the transaction process.

Table 2: Association between Firm Sales and Patents

Dependent Variable	Firm sales				
	All Firms (1)	All Firms (2)	Multinational (3)	Multinational (4)	Multinational (5)
Cumulative patents (own)	0.112***	0.055***	0.100***	0.097***	0.041***
	(0.007)	(0.005)	(0.020)	(0.020)	(0.015)
Cumulative patents (foreign parents)				0.123***	0.076***
				(0.023)	(0.018)
Firm-level Controls	No	Yes	No	No	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Obs	1,519,236	1,508,320	166,592	166,592	165,785
R-squared	0.891	0.908	0.890	0.890	0.912

Notes: In this table, we present the results from regression (1). The dependent variable is in logs, while the independent variables, cumulative patent numbers, are measured post IHS transformation. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). Standard errors are clustered at the firm level in case that there may be autocorrelation of errors. Significance levels: 10% *, 5% **, and 1% ***.

of patents applied by multinational affiliates between 2000 and 2015 were licensed to domestic firms, and the percentage drops to 0.11% for their foreign parent firms' patents.[11] Overall, the evidence indicates that there were direct technology transfers from multinational activities to domestic firms, albeit modest in terms of percentages. In the quantitative model, we will use this empirical evidence on technology transfers to discipline the magnitude of Quid Pro Quo policy.

Indirect Technology Transfers through Joint Ventures. A large body of evidence suggests that technology transfers usually occur through joint ventures (JVs). For example, Holmes, McGrattan and Prescott (2015) explore names on patent applications, showing that for the patents jointly owned by a foreign multinational and a local Chinese partner, the property rights of the Chinese partners stop at the border. This confirms that these technologies come out of the various joint ventures that foreign firms have been forced into as a requirement for obtaining market access. Bai et al. (2020) find evidence on a more micro level, showing that in China's automobile industry, the domestic entities involved in joint ventures enhanced the quality of their vehicles by assimilating knowledge from their foreign partners. The study by Jiang et al. (2024) presents ample empirical data regarding technology transfers within joint ventures, demonstrating a marked increase in productivity among Chinese partner firms subse-

[11] According to the survey (Zuniga and Guellec, 2009), patent license is used more as a tool to establish a technological monopoly rather than a technology exchange.

Table 3: Patent Activities between Local and Multinational Firms

Panel A: Patent Transactions	Sold to Domestic Firm		Sold to Multinational Affiliate			
	Count	Fraction	Count	Fraction	Only JVs	Fraction (JVs)
Multinational Affiliate:	13,400	10.45%	3,478	2.71%	1,032	0.80%
Joint Ventures	5,174	11.78%	512	1.17%	333	0.76%
Foreign Parent Firm	9,332	2.26%	914	0.22%	690	0.17%
Panel B: Patent Licensing	Licensed to Domestic Firm		Licensed to Multinational Affiliate			
	Count	Fraction	Count	Fraction	Only JVs	Fraction (JVs)
Multinational Affiliate:	544	0.42%	162	0.13%	40	0.03%
Joint Ventures	287	0.65%	59	0.13%	30	0.07%
Foreign Parent Firm	447	0.11%	625	0.15%	141	0.03%

Notes: We identify domestic firms as firms that are not multinational affiliates or foregn parent firms. "Fraction" refers to the percentage of all the patents applied by the corresponding firm group during the 2000–2015 period.

quent to their engagement in such ventures.

In our data, joint ventures accounted for 39% of patents filed by multinational affiliates between 2000 and 2015. Given the role of joint ventures in transferring technologies (which are not fully captured by transactions and licenses), in the baseline calibration of the quantitative analysis, we will consider all patents held by joint ventures as also being transferred to the Chinese party and reflecting Quid Pro Quo policy.

Technology Spillovers. To examine the impact of technology spillovers, we take advantage of the spillover measure suggested by Bloom, Schankerman and Van Reenen (2013), as it provides an empirical method to quantify the influence of spillover effects on innovation. The idea of this measure is that a firm potentially benefits more from other firms whose technology bundles are more similar to the firm's technology bundle. We define the vector $\mathbf{T}_i = (T_i^1, T_i^2, ..., T_i^{132})$, where T_i^τ is the share of firm i's patents in the technology class indexed by τ. We consider 132 3-digit IPC categories as technology classes (see Appendix B.3 for details on IPC classification). For firm i and firm j, we construct the similarity between two firms' technology bundles according to Jaffe (1986):

$$\rho_{ij} = \frac{\mathbf{T}_i \mathbf{T}_j^{'}}{\left(\mathbf{T}_i \mathbf{T}_i^{'}\right)^{1/2} \left(\mathbf{T}_j \mathbf{T}_j^{'}\right)^{1/2}}. \tag{2}$$

Thus, the index ρ_{ij} ranges between 0 and 1 and is closer to 1 if firms i and j have more patent applications in the same technology class. We compute ρ_{ij} between each local firm and each of multinational affiliates (their parent firms), using their cumulative patent applications up to 2015. With this index, we can compute the technology spillover from multinational affiliates and their foreign parent firms:

$$fdi\_spillover_{it} = \sum_{j \in \mathbb{M}} \rho_{ij} \times patent_{jt}, \qquad par\_spillover_{it} = \sum_{j \in \mathbb{I}} \rho_{ij} \times patent_{jt}, \tag{3}$$

where $\mathbb{M}$ and $\mathbb{I}$ denote the set of multinational affiliates and their foreign parent firms, respectively. $patent_{jt}$ is the amount of patent applications for firm j in year t.[12]

We then perform a regression similar to equation (1) to understand how technology spillovers affect domestic firms' innovation:

$$y_{it} = \beta_1 arcsinh(fdi\_spillover_{it}) + \beta_2 arcsinh(par\_spillover_{it}) + \alpha \mathbf{X}_{it} + \mu_i + \gamma_{s(i),t} + \epsilon_{it} \tag{4}$$

where the dependent variable y_{it} measures firm i's innovation activities in year t. We still perform this regression for manufacturing firms in 2000–2007.

Table 4 reports the regression results. To ensure consistency with our independent variables, we employ the number of patent applications post IHS transformation as the dependent variable in Columns (1)–(4) (the results using log1plus are robust as reported by Appendix Table A.4). In Column (1), we control for firm fixed effects and industry-year fixed effects, where industry-year fixed effects capture the effects of direct product market competition induced by multinational entry (we focus on the finest 4-digit industry classification). In Column (2), we further add firm-level controls (capital, employment, and ownership). We always find a positive association between domestic firms' patenting activities and their technology spillovers from multinational affiliates and their foreign parent firms.

The OLS regressions would be biased if multinational affiliates' entry happens disproportionately in the technology fields where domestic firms have comparative disadvantages (Alviarez, 2019). To lessen the endogeneity concern, we construct a

[12]Bloom, Schankerman and Van Reenen (2013) use the stock of R&D for firm j in year t to measure the source of spillovers. As we lack R&D data for most of the firms, we instead use the number of patent applications for firm j in year t. Given that patent applications may take a few years, we find that our results are robust if we use the cumulative amount of patent applications for firm j in year t in constructing $patent_{jt}$.

[13]Adao, Kolesár and Morales (2019) provide evidence that traditional approaches for computing standard errors, such as clustering, can exhibit bias when Bartik instruments are present. They propose an algorithm for correcting standard errors in the presence of one Bartik instrument. However, in our study, we have two Bartik instruments, making it impractical to directly apply the algorithm. Therefore, we utilize bootstrap standard errors following Goldsmith-Pinkham, Sorkin and Swift (2020), which allow for flexible structure of standard errors, to address potential bias.

Table 4: Association between Technology Spillovers and Domestic Firms' Innovation

Dependent Variable	Number of patent applications				Innovation status (patent application>0)			
	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)	OLS (5)	OLS (6)	2SLS (7)	2SLS (8)
Spillovers from MNE affiliates	0.035***	0.035***	0.013	0.118***	0.023***	0.023***	0.034**	0.033**
	(0.002)	(0.002)	(0.035)	(0.037)	(0.002)	(0.002)	(0.017)	(0.016)
Spillovers from foreign parents	0.059***	0.059***	0.346***	0.391**	0.044***	0.044***	0.129**	0.203**
	(0.005)	(0.006)	(0.117)	(0.174)	(0.004)	(0.004)	(0.054)	(0.102)
Firm-level Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,372,973	1,353,054	1,353,054	1,353,054	1,372,973	1,353,054	1,353,054	1,353,054
R-squared	0.015	0.015	0.000	0.000	0.013	0.013	0.000	0.000
Instrument			ind shift	WTO			ind shift	WTO
First-stage F			563.76	231.44			563.76	231.44

Notes: In this table, we present the results from regression (4). The dependent variable for Columns (1)–(4) is post IHS transformation, and the independent variables, spillover effects, are also measured post IHS transformation. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). In Columns (4) and (8), we also control for the firm's exposure to the industry-level determinants of the FDI policy changes as found by Lu, Tao and Zhu (2017) (see footnote 14 for details). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms.[13] Significance levels: 10% *, 5% **, and 1% ***.

Bartik-type instrument:

$$iv\_fdi\_spillover^1_{it} = \sum_s \left(\sum_{j \in \mathbb{M}_s} \rho_{ij} \times patent_{j,2000} \right) \frac{fdi\_firmnum_{s,t}}{fdi\_firmnum_{s,2000}}. \tag{5}$$

Here, we first compute the firm's spillovers from multinational affiliates in each 4-digit industry s in 2000, $\sum_{j \in \mathbb{M}_s} \rho_{ij} \times patent_{j,2000}$. Then, we predict the firm's overall spillovers from multinational affiliates in each year by combining the firm's industry-level spillovers in 2000 and industry-level growth in the number of multinational affiliates between 2000 and year t.

Our instrument aims to capture plausibly exogenous supply-driven variation in technology spillovers from multinational affiliates. The identification of shift-share instruments in the form of equation (5) can be obtained if the shifts are randomly assigned (Borusyak, Hull and Jaravel, 2022). In our case, as we control for firm fixed effects, the identification holds if industry-level growth in the number of multinational affiliates is orthogonal to changes in domestic firms' patenting activities. This assumption of identification is more likely to be true if the multinational entry is driven by policy changes. Thus, we also follow Lu, Tao and Zhu (2017) to exploit plausibly exogenous changes in FDI entry barriers after China's WTO accession:

$$iv\_fdi\_spillover^2_{it} = \sum_s \left(\sum_{j \in \mathbb{M}_s} \rho_{ij} \times patent_{j,2000} \right) \times encourage_s \times post\_WTO_t, \qquad (6)$$

where $encourage_s$ is a dummy variable indicating whether foreign investments in industry s became encouraged after China's WTO accession, as obtained by comparing "Catalogue for the Guidance of Foreign Investment Industries" between 1997 and 2002. $post\_WTO_t$ is a dummy variable indicating the post-WTO period (after 2002). The identification relies on the assumption that FDI policy changes are orthogonal to changes in domestic firms' patenting activities. To avoid that FDI policy changes may capture other industry-level characteristics that could produce spillover effects, we also control for the firm's exposure to the industry-level determinants of the FDI policy changes as found by Lu, Tao and Zhu (2017).[14]

In Columns (3)–(4), we perform the IV regressions by separately applying the instruments constructed in equations (5) and (6) (we analogously construct the instruments for the firm's spillovers from foreign parent firms). We still find a positive impact of technology spillovers from multinational affiliates or their foreign parent firms on domestic firms' patenting activities. The IV coefficients appear to be larger than the OLS coefficients, as the OLS coefficients may be biased downwards due to the possible negative correlation between multinationals' entry and domestic technology levels.

In Columns (5)–(8) of Table 4, we use innovation status (1 if the firm has positive patent applications) as the dependent variable. We still find a positive impact of technology spillovers from multinationals on domestic patenting activities. In Appendix Table A.5, we replace dependent variables with firm sales and TFP levels, which are alternative measures for firms' technology levels. We still find that there are positive associations between firms' sales (or TFP) and technology spillovers from multinational affiliates or their foreign parent firms. Given the concerns of using the logarithm transformation of count data (Silva and Tenreyro, 2006; Cohn, Liu and Wardlaw, 2022),[15] in

[14]Lu, Tao and Zhu (2017) identify four industry-level determinants $Z_{s,1998}$ of the FDI policy changes between 1997 and 2002: new product intensity, export intensity, number of firms, and average age of firms. For each determinant $Z_{s,1998}$, we construct the firm-level exposure to this determinant as:

$$x_i = \sum_s \left(\sum_{j \in \mathbb{M}_s} \rho_{ij} \right) \times Z_{s,1998} \times encourage_s \times post\_WTO_t.$$

where we weight the firm-level exposure to other industries' characteristics by technology similarity to be consistent with equation (6).

[15]We do not use Poisson regressions as suggested by Silva and Tenreyro (2006) because our indepen-

Appendix Table A.6,[16] we perform the regressions using levels of patent numbers and technology spillovers. We still find a positive impact of technology spillovers from multinational affiliates or their foreign parent firms on domestic firms' patent numbers. Given these pieces of evidence, in the quantitative model, we will thus explicitly model the impact of multinationals' knowledge spillovers on domestic firms' innovation and use our empirical evidence to discipline its magnitude.

It is worth noting that in the previous regression analyses, industry-year fixed effects were utilized to capture the competition effects caused by multinational affiliates. In Appendix Table A.7, we instead separately control for year and industry fixed effects, and we include the yearly share of multinational affiliates' sales in the total industry-level sales as an additional variable in the regression. Confirming the findings of Lu, Tao and Zhu (2017), we find that direct competition from multinational affiliates had a detrimental impact on innovation and productivity of domestic firms. Nevertheless, we still find a positive influence of technology spillovers from multinational affiliates and foreign parent firms on domestic firms' technology.

3 Model

To interpret our empirical results and conduct a quantitative analysis, we build a Ricardian model of trade, multinational production, and innovation. The world has I countries (indexed by i or j). In every nation, there exist a number of workers involved in either production or research and development (R&D). Additionally, each country harbors entrepreneurs who innovate, generating ideas that can be utilized for production domestically or abroad. The process of transferring ideas to foreign countries incurs fixed costs and may entail adherence to "Quid Pro Quo" policies in host nations, mandating the transfer of technology to local firms. Moreover, we incorporate knowledge spillovers by positing that increased knowledge enhances the efficiency of domestic innovation within the host country.

dent variables (spillovers from multinational affiliates) contain zero values.

[16] In Appendix Table A.6, we combine multinational affiliates' and their foreign parent firms' spillovers together as the independent variable. This aims to ease calibration in the quantitative analysis, in which we consider aggregate spillovers from both multinationals' knowledge brought into China and their knowledge created in China. The results are similar if we separately include spillovers from multinational affiliates and spillovers from their foreign parent firms in the regressions.

3.1 Workers' Preferences

Each country i is populated by a measure L_{it} of homogeneous workers in period t. A worker's utility in period t depends on its consumption level:

$$U = \ln X_{it}. \tag{7}$$

X_{it} is the consumption of the final goods.

Each worker supplies one unit of labor in each period, and the market wage rate is given by W_{it}. We do not consider intertemporal borrowing, implying that workers allocate all their current incomes toward purchasing the final good, $X_{it} = W_{it}/P_{it}$, where P_{it} is the aggregate price index of the final good.

3.2 Production

3.2.1 Final-good Production

There is a nontradable final good in each country, which is assembled by perfectly competitive firms using a constant elasticity of substitution (CES) function over a unit measure of varieties $\omega \in [0, 1]$:

$$Y_{it} = \left(\int_0^1 y_{it}(\omega)^{(\sigma-1)/\sigma} d\omega \right)^{\sigma/(\sigma-1)}. \tag{8}$$

$y_{it}(\omega)$ is the quantity of variety ω used in country i, and σ is the elasticity of substitution between varities. As in Eaton and Kortum (2002), for each variety, the final-good producer will search for the cheapest supplier from all over the world. The aggregate price index is $P_{it} = \left[\int_0^1 p_{it}(\omega)^{1-\sigma} d\omega \right]^{1/(1-\sigma)}$, where $p_{it}(\omega)$ is the (cheapest) price of variety ω sold in country i.

3.2.2 Multinational Production of Tradable Varieties

We model multinational production following Ramondo and Rodríguez-Clare (2013). Firms originating from country i can potentially produce each variety ω in each host country j. The production uses labor l with the following production function:

$$y_{ijt}(\omega) = A_{ijt} z_{ijt}(\omega) l \tag{9}$$

A_{ijt} is the aggregate productivity of firms originating from country i and producing in j. This productivity may account for various factors, such as disparities in patent quality or efficiency losses associated with cross-country knowledge flows (Alviarez, Cravino and Ramondo, 2023), and therefore might not directly correspond to the productivity level in the firm's home country. In our quantitative analysis, we treat A_{ijt} as exogenously given. $z_{ijt}(\omega)$ is the idiosyncratic productivity draw from Frechet distribution $F_{ijt}(z) = \exp(-T_{ijt}z^{-\vartheta})$. T_{ijt} is the stock of ideas, which is endogenously determined by the innovation process, as we will describe below.

3.2.3 International Trade

Varieties can be traded across countries. We assume that the iceberg costs between host country i and destination j is $\tau_{ijt} \geqslant 1$, which implies that shipping one unit of good from country i to j incurs a $(\tau_{ijt} - 1)$ loss of units in transportation, with iceberg costs of selling to the domestic market, $\tau_{iit} = 1$. Thus, the unit cost of serving country k for a producer with productivity draw $z_{ijt}(\omega)$ originating from country i and producing in j is given by:

$$c_{ijkt}(\omega) = \frac{W_{jt}\tau_{jkt}}{A_{ijt}z_{ijt}(\omega)}. \tag{10}$$

The innovation efforts are incentivated by profits from production. Following the assumptions of Bernard et al. (2003), we consider producers to be engaged in Bertrand competition, which facilitates aggregation as also exploited in recent papers that study trade and innovation in a Ricardian model (Somale, 2021; Cai, Li and Santacreu, 2022). More specifically, in Bertrand competition, final-good producers in country k will procure a particular variety ω from the producer across the world who has the lowest unit cost for serving country k. The price charged for the variety will be determined by the lower value between the monopoly price and the second-lowest costs, thus featuring variable markups across firms.

Given these assumptions, the share of final-good expenditures in country k spent on varieties produced in country j by producers originating from country i is given by a gravity equation:

$$\Pi_{ijkt} = \frac{T_{ijt}(W_{jt}\tau_{jkt}/A_{ijt})^{-\theta}}{\sum_{i',j'} T_{i'j't}(W_{j't}\tau_{j'kt}/A_{i'j't})^{-\theta}}. \tag{11}$$

As one would anticipate, the trade share rises in the presence of higher knowledge stock T_{ijt} and aggregate productivity A_{ijt}. Conversely, it decreases in response to higher wage costs W_{jt} and bilateral trade costs τ_{jkt}. As shown in Bernard et al. (2003), the variable costs account for $\frac{\theta}{1+\theta}$ of aggregate revenues, whereas profits account for the remaining $\frac{\theta}{1+\theta}$ of revenues. Finally, the price index of the final good is given by:

$$P_{kt} = \gamma \left[\sum_{i,j} T_{ijt} (W_{jt} \tau_{jkt} / A_{ijt})^{-\theta} \right]^{-1/\theta}, \tag{12}$$

where $\gamma = \left[\left(1 + \frac{(\sigma-1)^{\theta+1}}{\sigma^{\theta}(1+\theta-\sigma)} \right) \Gamma\left(\frac{1+2\theta-\sigma}{\theta} \right) \right]^{1/(1-\sigma)}$ is a constant.

3.3 Innovation

Idea Creation. In the preceding section, we demonstrated that the vector of knowledge stock $\mathbb{T}_t = \{T_{ijt}\}$ influences the arrangement of multinational production and trade. We now discuss how $\mathbb{T}_t$ evolves due to idea creation and transfers, which brings *dynamics* into the model through the evolution of knowledge stock between periods. As the count of patents from foreign parent firms significantly outnumbers the patents from multinational affiliates in our data, our baseline model focuses primarily on the innovation of parent firms, thus simplifying the model derivation and being consistent with the literature (Arkolakis et al., 2018).[17] In Section 5.4, we examine the robustness of quantitative findings when affiliate innovation is taken into account.

In country i, we assume that there is a continuum of entrepreneurs who hire researchers to produce new ideas. The Poisson arrival rate of new ideas is given by:

$$A^e_{it} \left(\sum_j \phi_{ji} T_{jit} \right)^{\mu} (L^e_{it})^{\gamma}, \tag{13}$$

Here A^e_{it} is research efficiency in country i. Aside from modeling the dependence of the arrival rate on domestic knowledge stock, which ensures endogenous growth (Eaton and Kortum, 1999), we also consider that the arrival rate depends on spillovers from the knowledge brought by multinationals from country j into i, $T_{jit},\ j \neq i$, with ϕ_{ji} capturing the importance of knowledge from j (we normalize domestic spillovers $\phi_{ii} = 1\ \forall\ i$), and $\mu > 0$ capturing the curvature. The introduction of this feature is not only guided by our empirical fact, but also inspired by research showing agglom-

[17] Aligned with our evidence from China, similar patterns are evident in other nations where the innovation of parent firms carries greater significance compared to that of affiliates. For instance, research utilizing data from the US Census Bureau, as demonstrated by Liu (2024), reveals that offshore R&D contributes approximately 20% to the innovation of US companies.

eration effects of innovation as reviewed by Carlino and Kerr (2015) and that trade induces technology diffusion across countries (e.g., Alvarez, Buera and Lucas, 2013; Perla, Tonetti and Waugh, 2015; Sampson, 2016; Buera and Oberfield, 2020).[18] Finally, L^e_{it} is the amount of R&D workers, and $0 < \gamma < 1$ governs the diminishing returns to innovation as found in the literature (see Acemoglu et al. (2018) for a review).

Each new idea pertains to a technology for producing a single variety of good, randomly drawn from $[0, 1]$. It is also characterized by a productivity level, which is a random draw of the Pareto distribution $G(z) = 1 - z^{-\theta}$. The new idea can always be utilized in the local market. With a uniform productivity distribution across ideas, a new idea created in country i has a probability of $1/T_{iit}$ to emerge as the superior idea in a variety among the domestically created ideas up to time t.

Utilization of Ideas Abroad and Quid Pro Quo Policy. Upon generating a new idea, entrepreneurs in country i also have the option of taking their idea to any other location $j \neq i$ for production (e.g., Tesla established a plant in Shanghai to produce Model Y vehicles). Bringing technology to overseas incurs two types of costs. First, bringing an idea to a foreign market induces a fixed cost $f_t x$ in units of final goods in the originating country, where $f_t > 0$ is a parameter, and $1/x$ is a random variable that is distributed i.i.d. across varieties according to Pareto distribution $1 - y^{-\kappa}$. Modeling fixed costs follows from Arkolakis et al. (2018), allowing entrepreneurs to only bring profitable ideas to overseas,[19] whereas the random component of fixed costs eases aggregation. Second, conditional on bringing an idea to country j, we also consider that an entrepreneur potentially faces the "Quid Pro Quo" policy. We denote q as the intensity of using idea, following Holmes, McGrattan and Prescott (2015). If an entrepreneur utilizes $q \in [0, 1]$ of the newly developed idea from country i to $j \neq i$, a portion $\eta_j q^{\psi}$ of the idea will be transferred to domestic producers in country j ($\eta_j \geqslant 0$). $\psi > 1$ captures that the technology transfer rate is a convex function of the transfer rate, aligning with the evidence indicating that larger firms have a greater chance of encountering Quid Pro Quo policies (Holmes, McGrattan and Prescott, 2015).

We consider that the movement of ideas across borders happens before the productivity draws are realized. Moreover, we assume that the productivity level of

[18]For example, in a model calibrated to cross-country data, Buera and Oberfield (2020) find that the gains from trade more than double after introducing the diffusion of ideas between competitors from different countries. Considering the significant role multinational production plays in globalization, it is therefore natural to speculate that it also generates knowledge spillovers.

[19]This feature enables the model to capture the observation that only half of the granted patents originating from a country have been patented in other countries.

an idea is location-specific and independent across locations. This assumption ensures that for each destination market, the best and second-best costs maintain the Frechet distribution as developed by Bernard et al. (2003), which facilitates the aggregation and ensures a constant aggregate markup. Whereas the assumption is made for tractability, it captures the varying applicability of the same technology across countries, possibly relying on many location-specific factors (Acemoglu and Zilibotti, 2001) or consumers' different preferences for goods produced in different locations as in the Armington model. This assumption is also consistent with recent evidence on multinational production in Garetto, Oldenski and Ramondo (2021), who show that the US affiliate entry follows a weak "extended gravity" pattern.[20]

Evolution of Idea Stock After describing the creation and international flows of ideas, we can now characterize the change in the idea stock over time:

$$\Delta T_{ijt} = \begin{cases} A^e_{jt}\left(\sum_{i'} \phi_{i'j} T_{i'jt}\right)^{\mu} \left(L^e_{jt}\right)^{\gamma} + \eta_j \sum_{i' \neq j} q^{\psi+1}_{i'jt} O_{i'jt} A^e_{i't} \left(\sum_k \phi_{ki'} T_{ki't}\right)^{\mu} \left(L^e_{i't}\right)^{\gamma} & \text{if } i = j \\ (1 - \eta_j q^{\psi}_{ijt}) q_{ijt} O_{ijt} A^e_{it} \left(\sum_k \phi_{ki} T_{kit}\right)^{\mu} \left(L^e_{it}\right)^{\gamma} & \text{if } i \neq j, \end{cases} \tag{14}$$

where $\Delta T_{ijt} = T_{ijt+1} - T_{ijt}$ reflects changes in the number of ideas. O_{ijt} is the share of ideas brought to country j among all the ideas created in country i, and conditional on ideas being brought, q_{ijt} is the intensity of using ideas, as derived below. The first line of equation (14) indicates that the growth of the host country's local knowledge stock is not only contingent upon domestic knowledge creation but also on technology transfers from multinational firms, particularly when the host country adopts Quid Pro Quo policies. In contrast to existing literature that typically assumes the cross-border diffusion of knowledge to be exogenous (e.g., Jones, 2002; Klenow and Rodríguez-Clare, 2004), our model endogenously determines knowledge flows between countries via multinational corporations' tradeoff between profits from using ideas, fixed costs of using ideas, and potential losses of technology to local firms.

The idea stock in $t + 1$ is $T_{ijt+1} = T_{ijt} + \Delta T_{ijt}$. Given the Poisson arrival process of ideas and that each idea's productivity follows the Pareto productivity, for each

[20] Garetto, Oldenski and Ramondo (2021) observe that for a given US parent, there is an extremely small difference between the unconditional probability of opening an affiliate in a country and the probability of opening an affiliate conditional on already having an affiliate in a country located in the same continent, or in a country with similar income per capita. This evidence is consistent with independent productivity draws across locations.

variety, we can characterize the productivity distribution of the best idea as:

$$F_{ijt+1}(z) = \sum_{k=0}^{\infty} \frac{(T_{ijt+1})^k e^{-T_{ijt+1}}}{k!} G(z)^k = e^{-T_{ijt+1}(1-G(z))} = e^{-T_{ijt+1}z^{-\theta}}. \tag{15}$$

Here, $\frac{(T_{ijt+1})^k e^{-T_{ijt+1}}}{k!}$ represents the probability of having k ideas with a Poisson arrival rate of T_{ijt+1}, while $G(z)^k$ represents the probability of the best idea having a productivity below z given k ideas. Therefore, the distribution of productivity resulting from the evolution of ideas aligns with our assumption regarding the productivity distribution of varieties outlined in Section 3.2.2. Somale (2021) demonstrates that equation (15) also implies a Frechet productivity distribution for the best and second-best productivity levels, as utilized by Bernard et al. (2003) to model Bertrand competition.

Solving Optimal Choices of Idea Utilization and Creation. To begin with, we follow Eaton and Kortum (2001) to define the aggregate value per unit of idea originating from country i and used in host country j for a new idea developed in time t:

$$V_{ijt} = P_{it} \sum_{\tau=t+1}^{\infty} e^{-\rho(\tau-t)} \frac{1}{P_{i\tau}} \frac{R_{ij\tau}}{T_{ij\tau}} \frac{1}{1+\theta}. \tag{16}$$

ρ is the discount rate. $R_{ijt} = \sum_k \Pi_{ijkt} E_{kt}$ is the total revenue for ideas originating from country i and used in host country j, with E_{kt} being the total expenditures in country k. $\frac{R_{ij\tau}}{T_{ij\tau}}$ is the revenue per unit of idea, and $\frac{1}{1+\theta}$ is the ratio of profits to revenues.

For each idea generated in country i in time t, we first solve whether the entrepreneur brings it to country j, indexed by a dummy $\mathcal{I}$, and the intensity of using ideas, q_{ijt}, to maximize profits from bringing each unit of idea overseas:

$$\max_{\mathcal{I}\in\{0,1\}, q\in[0,1]} \mathcal{I}\left[(1-\eta_j q^{\psi}) q V_{ijt} - f_t x P_{it}\right] \tag{17}$$

This implies:

$$q_{ijt} = \begin{cases} \min\left\{ \left(\frac{1}{\eta_j(\psi+1)}\right)^{1/\psi}, 1\right\} & \text{if } \eta_j > 0 \\ 1 & \text{if } \eta_j = 0 \end{cases}, \quad \mathcal{I} = \begin{cases} 1 & \text{if } (1-\eta_j q_{ijt}^{\psi}) q_{ijt} V_{ijt} - f_t x P_{it} \geqslant 0 \\ 0 & \text{otherwise.} \end{cases} \tag{18}$$

Given the Pareto distribution of $1/x$ across varities, we can obtain the share of ideas brought to country j among all the ideas created in country i:

$$O_{ijt} = \min\left\{ \left(\frac{(1-\eta_j q_{ijt}^{\psi}) q_{ijt} V_{ijt}}{f_t P_{it}} \right)^{\kappa}, 1 \right\}. \tag{19}$$

Equations (18) and (19) suggest that implementing a more stringent Quid Pro Quo Policy in country j (indicated by a higher η_j value) would decrease both the intensity of idea flows and the proportion of ideas sourced from country j. Conversely, greater profits available from utilizing ideas in country j would serve as an incentive for increased idea flows to that location.

Finally, we can describe the optimal selection of R&D workers L_{it}^e:

$$\frac{W_{it}}{\gamma A_{it}^e \left(\sum_j \phi_{ji} T_{jit}\right)^{\mu} (L_{it}^e)^{\gamma-1}} = V_{iit} + \sum_{j\neq i} \left[(1-\eta_j q_{ijt}^{\psi}) q_{ijt} O_{ijt} V_{ijt} - \frac{\kappa O_{ijt}^{(\kappa+1)/\kappa} f_t P_{it}}{\kappa+1} \right] \tag{20}$$

which implies that the marginal cost of generating new ideas (left-hand side) aligns with the marginal benefit of adding another idea (right-hand side).[21]

3.4 Equilibrium

We assume that trade is balanced in each period, and entrepreneurs spend all their profits on final goods in their original country. The labor-market clearing in time t requires:

$$L_{it} = L_{it}^y + L_{it}^e, \tag{21}$$

where L_{it}^y is the total amount of production workers in country i. The good-market clearing condition for country i in time t requires:

$$\frac{(1+\theta)}{\theta} W_{it} L_{it}^y = \sum_j \sum_k \Pi_{jikt} E_{kt}. \tag{22}$$

$R_{it} = \frac{(1+\theta)}{\theta} W_{it} L_{it}^y$ is the aggregate revenue of producers in country i, as variable costs account for $\frac{\theta}{1+\theta}$ of revenues. The aggregate revenue shall equal the weighted average of expenditures from all over the world (weighted by trade shares). Expenditures

[21] $\frac{\kappa O_{ijt}^{(\kappa+1)/\kappa} f P_{it}}{\kappa+1}$ is the aggregated fixed costs among all the ideas that are brought to country j.

(incomes) in country k are

$$E_{kt} = W_{kt}L^{y}_{kt} + \frac{1}{1+\theta}\sum_{j}\sum_{i}\Pi_{kjit}E_{it}, \tag{23}$$

which equals gross profits and production workers' wage income. Gross profits include wage income for research workers, fixed costs of bringing ideas to other countries, and entrepreneurs' net profits, all of which are eventually spent on final goods.

As the dynamics between periods only involve changes in knowledge stock, we can obtain the model equilibrium using the following steps. First, for each period, given knowledge stock vector $\mathbb{T}_t$ and the amount of R&D workers L^{e}_{it}, we can solve trade shares Π_{ijkt}, aggregate price P_{it}, wage rate W_{it}, and expenditures E_{kt} from equations (11), (12), (22), and (23). Second, given the sequences of $\{\Pi_{ijkt}, P_{it}, W_{it}, E_{kt}\}$ over time, we obtain the optimal amount of R&D workers L^{e}_{it}, the optimal idea utilization q_{ijt}, the share of ideas brought O_{ijt}, and the evolution of idea stock $\mathbb{T}_t$ from equations (14), (17), (19), and (20). We iterate on these two steps until the convergence of endogenous variables $\{\Pi_{ijkt}, P_{it}, W_{it}, E_{kt}, L^{e}_{it}, q_{ijt}, \mathbb{T}_t\}$. In Appendix C.1, under some assumptions, we characterize the balanced growth path of this economy, where the accumulation of ideas leads to constant positive growth in knowledge stock and real income. In Appendix D.4, we outline the solving algorithm for the general model.

3.5 Main Mechanisms

Impact of Multinationals on Domestic Technology. Using the above framework, we can now characterize the growth rate of domestic knowledge stock in country i:

$$g_{iit} = \frac{\Delta T_{iit}}{T_{iit}} = A^{e}_{it}\frac{\left(\sum_j \phi_{ji}T_{jit}\right)^{\mu}}{T_{iit}}(L^{e}_{it})^{\gamma} + \eta_i\sum_{j\neq i} q^{\psi+1}_{jit}O_{jit}A^{e}_{jt}\frac{\left(\sum_k \phi_{kj}T_{kjt}\right)^{\mu}}{T_{iit}}(L^{e}_{jt})^{\gamma} \tag{24}$$

where L^{e}_{it} can be solved from equation (20) as:

$$L^{e}_{it} = \left\{\frac{\gamma A^{e}_{it}\left(\sum_j \phi_{ji}T_{jit}\right)^{\mu}\left[V_{iit} + \sum_{j\neq i}\left((1-\eta_j q^{\psi}_{ijt})q_{ijt}O_{ijt}V_{ijt} - \frac{\kappa O^{(\kappa+1)/\kappa}_{ijt} f_t P_{it}}{\kappa+1}\right)\right]}{W_{it}}\right\}^{1/(1-\gamma)}. \tag{25}$$

We can obtain the following result characterizing the impact of multinationals on domestic technology growth:

Result 1 (Impact of Multinationals on Domestic Technology) *All else being equal:*
(1) local technology growth g_{iit} increases with the strength of knowledge spillovers of multinationals' knowledge, ϕ_{ji}; and
(2) local technology growth g_{iit} decreases if the value from the domestic market V_{iit} is lower.

Proof: See Appendix C.2.

Result 1 illustrates two opposite impacts of multinationals on domestic technology advancement. On one hand, the knowledge spillovers from multinational firms can reduce innovation costs and stimulate greater innovation efforts. On the other hand, multinational entry can heighten local market competition and decrease domestic firms' revenues, which, in turn, may reduce the incentives for domestic firms to engage in innovation activities. This reflects the Schumpeterian effect, which posits that higher profits drive innovation (Schumpeter, 1942). Although these findings are derived under the partial equilibrium, we will numerically evaluate and analyze these results within a general equilibrium framework.

Gains from Multinational Production. We follow the literature (e.g., Ramondo and Rodríguez-Clare, 2013; Arkolakis et al., 2018) to consider the gains from multinational production, defined as the changes in real income as we move from a counterfactual equilibrium with no multinational production to the observed equilibrium.

Proposition 1 (Gains from Multinational Production) *The gains from multinational production are expressed as:*

$$GMP_{it} = \underbrace{\left[\left(\frac{\Pi_{iiit}}{\Pi_{iiit}^{TR}} \right)^{-1/\theta} \frac{E_{it}/R_{it}}{E_{it}^{TR}/R_{it}^{TR}} \right]}_{\text{static gains}} \underbrace{\left[\frac{1 - r_{it}}{1 - r_{it}^{TR}} \left(\frac{T_{iit}}{T_{iit}^{TR}} \right)^{1/\theta} \right]}_{\text{dynamic gains}} \tag{26}$$

where the superscript "TR" denotes the variables in trade-only models, and $r_{it} = L_{it}^{e}/L_{it}$ is the share of researchers in total employment in country i.

Proof: See Appendix C.3.

In the above proposition, the first bracket represents the static benefits stemming from multinational production given the stock of ideas. These benefits align precisely with the gains from trade that can be identified in a model featuring an exogenous idea stock and no innovation. This finding is consistent with Ramondo and Rodríguez-Clare (2013), suggesting that alterations in trade shares of domestically originated and producing firms, $\left(\frac{\Pi_{iiit}}{\Pi_{iiit}^{TR}}\right)^{-1/\theta}$, capture the changes in real wages for workers. Given that our model incorporates imperfect competition, we also consider variations in profits, which are not directly linked to domestic wages in the model featuring multinational production. These profit changes are captured through adjustments in the ratio of real income to production value E_{it}/R_{it} within our model.

The second bracket pertains to the dynamic benefits arising from multinational production. The first component $\frac{1-r_{it}}{1-r_{it}^{TR}}$ captures the shifts in the proportion of production workers, as increased innovation (which augments future output) results in fewer production workers and consequently less production in the present time. The second component $\left(\frac{T_{iit}}{T_{iit}^{TR}}\right)^{1/\theta}$ captures the changes in the stocks of ideas. These two terms are similarly derived by Arkolakis et al. (2018). The difference of our model is that the allowance for multinational entry does not only have effects on idea creation as in Arkolakis et al. (2018), but also has effects on idea stocks through knowledge spillovers and Quid Pro Quo policies. Furthermore, while Arkolakis et al. (2018) focuses on a one-period steady-state model, our model incorporates transitional dynamics, allowing for the accumulation of the impact of shocks to multinational entry on idea stock over time.

In Appendix C.4, we provide the formula for quantifying the gains from openness, representing the changes in real income that occur when transitioning from a counterfactual equilibrium without multinational production and trade to the observed equilibrium. Similar to equation (26), the gains from openness encompass both static gains arising from changes in real income (in relation to the existing stock of ideas) and dynamic gains stemming from alterations in innovation efforts and the stock of ideas.

4 Calibration

In this section, we describe the calibration procedure. We then discuss the model parameters and the model fit to the data moments.

4.1 Data

We calibrate our model to the manufacturing sector in 61 countries and regions,[22] along with a constructed rest of world. We focus on the period between 2000 and 2015, consistent with the period examined in our empirical analysis. Besides the aforementioned Chinese patent and firm data in Section 2, for regions other than China, we combine region-year-level value added, employment, trade, multinational production, and patent data to construct the relevant data moments. Appendix D.1 and D.2 provide details on the regions considered in our calibration and the data sources.

4.2 Calibration Procedure

We cannot solve the model using "Exact Hat" approach proposed by Dekle, Eaton and Kortum (2008), due to the complexities of entrepreneurs' innovation decisions and the lack of data on origin-host-destination trade flows. We thus calibrate the fundamental parameters of the model and now describe our calibration procedure.

4.2.1 Externally Calibrated Parameters

We first calibrate a set of parameters directly using the literature, the data, or estimation without relying on the model simulations, as listed in Table 5.

Parameters from the literature and the data. One period in the model is one year, and we set the discount rate $\rho = 0.05$. We directly obtain region-year employment level L_{it} from the data. For the elasticity of innovation returns to innovation efforts γ, we set $\gamma = 0.5$ according to the typical value used in the literature (see Acemoglu et al. (2018) for a review). We use the trade elasticity $\theta = 4.5$, which is the average of the values estimated by the literature according to the review in Head and Mayer (2014). The elasticity of substitution does not affect equilibrium outcomes as long as $\theta > \sigma - 1$ is satisfied, and thus we set $\sigma = 3$ according to Hsieh and Klenow (2009). We choose the curvature of spillovers in innovation $\mu = 0.05$ according to Moretti (2021), which also aligns with the parameterization in Holmes, McGrattan and Prescott (2015).

[22] We concentrate on the manufacturing sector as our model centers on innovation, and industrial firms are known to be the primary drivers of innovation, as supported by Ma (2023)'s findings in China and Akcigit and Kerr (2018)'s evidence in the US. Additionally, we limit our study to 61 countries/regions to ensure that we have access to sufficient patent and trade data.

Trade Costs from Estimating Gravity Equation. We estimate trade costs using trade data. To begin with, from the trade share in equation (11), we can obtain the relative trade shares in logarithms for estimation (Eaton and Kortum, 2002):

$$\log\left(\frac{\sum_i \pi_{ijkt}}{\sum_i \pi_{ikkt}}\right) = S_{jt} - S_{kt} - \theta \log \tau_{jkt}, \tag{27}$$

where fixed effects $S_{kt}^{j} = \log \sum_i T_{ikt} \left(W_{kt}/A_{ikt}\right)^{-\theta}$ measures the "competitiveness" of country k as a production location, aggregating production technologies across originating countries. For tractability of estimation, we also need to make functional restrictions on trade costs τ_{jkt}. We follow the literature (e.g., Head and Mayer, 2014) and assume that the trade costs take the following functional form:

$$\log \tau_{jkt} = \beta_{1t} \log dist_{jkt} + \beta_{2t} contig_{jkt} + \beta_{3t} \log GDPPC_{jt} + \epsilon_{jkt} \tag{28}$$

where $dist_{jkt}$ is the distance between capitals of two regions. $contig_{jkt}$ is a dummy variable indicating whether two regions are contiguous. Finally, we also allow trade costs to rely on GDP per capita of the exporting region, reflecting that poorer countries may have higher export iceberg costs as shown by Waugh (2010).[23]

We use bilateral trade data to estimate equation (27) for each year between 2000 and 2015. It is worth noting for many origin-destination pairs, trade shares are zero, and thus the dependent variable may be missing, biasing the estimates if we perform the OLS regression. Thus, we follow Silva and Tenreyro (2006) to estimate equation (27) using Poisson regression, allowing for zero bilateral trade flows. We recover yearly trade costs from the estimates:

$$\hat{\tau}_{jkt} = \exp\left(\hat{\beta}_{1t} \log dist_{jkt} + \hat{\beta}_{2t} contig_{jkt} + \hat{\beta}_{3t} \log GDPPC_{jt}\right).$$

4.3 Internally Calibrated Parameters

To reduce the number of parameters that require calibration, we make several assumptions. First, we assume aggregate productivity $A_{ijt} = A_{it}\lambda_{ijt}$. A_{it} is the fundamental

[23] In the study by Waugh (2010), a group of country-specific dummy variables is introduced to estimate export iceberg costs associated with development levels. However, due to the increase in estimation imprecision caused by introducing an additional full set of country-specific dummy variables (especially considering the estimation performed for each year), we opt to directly model trade costs as a function of GDP per capita.

Table 5: Parameter Values

Parameter	Notation	Value	Source
Panel A: Parameters Set without Solving the Model			
Discount rate	β	0.95	Interest rate
Elasticity of innovation returns to innovation efforts	γ	0.5	Acemoglu et al. (2018)
Trade elasticity	θ	4.5	Head and Mayer (2014)
Elasticity of substitution	σ	3	Hsieh and Klenow (2009)
Curvature of spillovers	μ	0.05	Moretti (2021)
Trade costs	τ_{jkt}	3.11 (0.67)	Data estimate
Panel B: Parameters Set by Solving the Model			
Fundamental productivity	A_{it}	0.64 (0.72)	
Productivity efficiency loss due to distance	ζ_d	0.08	
Adjustment parameter on efficiency loss	ζ	0.14	
China's Adjustment parameter on efficiency loss	$\zeta_{CN,t}$	0.20 (0.11)	
Innovation efficiency (log value)	$\log A^e_{it}$	8.47 (6.69)	
Constant in fixed costs of bringing ideas	f	1.1e-04	
Dispersion of fixed costs of bringing ideas	κ	2.32	
Strength of spillovers from multinationals to China	ϕ_{CN}	1.44	
China's Quid Pro Quo Policy	η_{CN}	1,015	
Convexity of technology transfer rate	ψ	7.70	

productivity of firms from country i, and λ_{ijt} captures the efficiency loss due to bringing knowledge to overseas.[24] In particular, we assume that $\lambda_{ijt} = \zeta dist_{ijt}^{-\zeta_d}$ if $j \neq CN$, and $\lambda_{ijt} = \zeta_{CN,t} dist_{ijt}^{-\zeta_d}$ if $j = CN$, where $\zeta_d > 0$ captures efficiency losses due to distance between originating and host countries (Ramondo, Rodríguez-Clare and Tintelnot, 2015). We consider parameter ζ to adjust efficiency losses due to distance, in order to match the level of efficiency losses observed in the data. We allow China to have a specific and time-varying adjustment parameter $\zeta_{CN,t}$, capturing China's time-varying FDI regulations for multinationals to produce in China. Second, we assume that the parameter governing fixed costs of bringing ideas is constant, $f_t = f$. Finally, due to the lack of data, we also only focus on knowledge spillovers from multinationals to China, $\phi_{ji} = 0$ if $j \neq i$ and $i \neq CN$, and $\phi_{ji} = \phi_{CN}$ if $j \neq i$ and $i = CN$. We also abstract from considering Quid Pro Quo policies in other countries, $\eta_j = 0\ j \neq CN$.

We are thus left with a set of parameters to calibrate internally: fundamental productivity of firms, A_{it}; productivity efficiency losses of multinational activities across borders $\{\zeta, \zeta_{CN,t}, \zeta_d\}$; innovation efficiency, A^e_{it}; parameter governing China's Quid Pro Quo policy, η_{CN}; parameters governing fixed costs of bringing ideas, $\{f, \kappa\}$; parameter governing knowledge spillovers from multinationals to China, ϕ_{CN}; and the convexity of technology transfer rate, ψ.

[24]We have $\lambda_{ijt} = 1$ if the firm produces in the originating market $j = i$.

Table 6: Moments in the Model and the Data

Moment	Data	Model
1. Manufacturing value added in each country and year (relative to US)	0.08 (0.20)	0.09 (0.20)
2. Elasticity of multinational affiliate sales to distance between originating and host countries	-1.14	-1.15
3. Ratio of multinational affiliate sales to host country's production	0.19	0.19
4. Ratio of multinational affiliate sales to China's total production in each year	0.15 (0.02)	0.15 (0.02)
5. Number of granted patents in each country and year (relative to initial year's number)	0.35 (1.00)	0.35 (1.00)
6. Elasticity of number of granted patents to distance between originating and host countries	-0.79	-0.76
7. Share of each country's granted patents being registered overseas	0.51	0.51
8. Fraction of multinationals' patents in terms of all patents in China granted by 2015	0.40	0.41
9. Proportional change in China's domestic knowledge without knowledge spillovers	-0.19	-0.17
10. Share of multinationals' knowledge transferred to China	0.12	0.12

We jointly calibrate these parameters using the simulated method of moments (SMM) by minimizing the absolute differences between the model moments and the data moments, as listed in Table 6 with detailed construction for the moments explained by Appendix D.3. In particular, we follow our earlier empirical analysis in Section 2 to use the number of patents as a proxy for knowledge stock. We also take advantage of the reduced-form evidence documented in Section 2.3 to inform the strength of knowledge transfers and spillovers.[25]

To gain insight into how the parameters are determined, it is helpful to note that some parameters have a more direct impact on specific moments. For instance, the productivity and innovation efficiency of firms originating from each country, $\{A_{it}, A_{it}^e\}$, directly influence GDP and the amount of granted patents by domestic firms in each country. The strength of knowledge spillovers from multinational firms to China's firms, ϕ_{CN}, is directly related to the proportional change in domestic firms' patent numbers in the absence of knowledge spillovers. Finally, the degree of the Quid Pro Quo policy in China, η_{CN}, can be inferred by the amount of multinationals' patents filed in China, as a higher value of η_{CN} results in multinationals being less inclined to introduce technology into China.

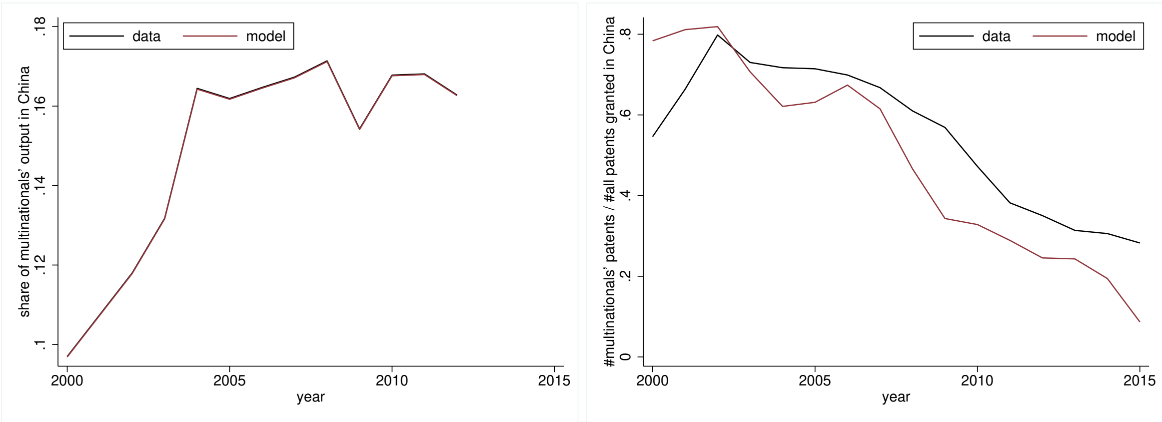
[25]To compute a comparable model moment regarding knowledge spillovers, we perform an experiment in the model by setting Chinese firms' knowledge spillovers from multinationals to zero, $\phi_{CN} = 0$, and then compute the model-based reduction in the number of innovations due to knowledge spillovers from multinationals. In the computation, we keep the general equilibrium variables constant, which is in line with our regressions in Section 2.3 that control for aggregate prices and quantities using a set of fixed effects. Our algorithm follows the recent development literature (Buera, Kaboski and Yongseok, 2021; Buera, Kaboski and Townsend, 2021) to use reduced-form evidence to discipline model parameters.

4.4 Calibration Results

Panel B of Table 5 displays the calibrated parameter values, which are reasonable compared to the existing literature. Specifically, because $\zeta_d > 0$, we find that multinational firms experience reduced productivity especially when they move to remote countries, consistent with the evidence in the literature (Keller and Yeaple, 2013; Ramondo, Rodríguez-Clare and Tintelnot, 2015). The strength of multinationals to China is $\phi_{CN} = 1.44$, implying that roughly 50% of the knowledge used in China's domestic innovation originates from multinational firms, consistent with evidence on domestic citation shares in China (Liu and Ma, 2023). Our calibrated Quid Pro Quo cost in China implies that the intensity of using ideas in China is 0.31, similar to the estimates by Holmes, McGrattan and Prescott (2015), who find the intensity of using technology capital for multinationals in China to be 0.35-0.41 in 2000–2010.

Table 6 confirms that our model closely matches all the targeted moments. As we focus on multinational firms in China, in Figure 3a, we show that the model matches the share of multinationals' output in China's total output, which is targeted mainly through disciplining parameters $\zeta_{CN,t}$, revealing China's time-varying FDI regulations. The graph reveals that China gradually became less restrictive to multinationals' production in the 2000s, consistent with the loosening of the FDI policy during this period. Figure 3b displays the fraction of multinationals' patents granted in China in terms of all patents granted in China in the corresponding year.[26] Even though our model only targets the overall fraction by 2015, our model matches the declines in the yearly fraction of multinationals' patents as found in the data. Despite increasing attractiveness to FDI firms due to the loosening of FDI policies, the decline was due to the surge of Chinese firms' innovation. In Appendix Figure A.2, we demonstrate that our model closely aligns with the region-year value added and innovation intensity, and this alignment can be well approximated by a 45-degree line.

[26] It is important to note that apart from patent grants from both multinational and domestic firms, there are additional foreign patents filed with China's patent office. However, due to limited information on the utilization of these foreign patents in domestic production, we do not include them in our quantitative analysis. Thus, the fraction in Figure 3b differs from Figure 1 because of excluding foreign patents that do not long to multinationals. Another small distinction lies in the fact that as our data moments regarding patents from other countries are based on the year of grant, we thus measure patents in China based on the year of grant in the calibration.



(a) Share of Multinationals' Output

(b) Share of Multinationals' Patents

Figure 3: Multinationals' Output and Patents in China in Model and Data

5 Quantitative Analysis

Equipped with the calibrated model, we conduct various experiments in this section to comprehend how multinational entry influences China's production and innovation.

5.1 China's Gains from Multinational Firms

We first quantify China's gains in production and idea stock from entry of multinational firms. To this end, we simulate a counterfactual scenario where we set $\zeta_{CN,t} = 0$ and $\phi_{CN} = 0$, resulting in no production and therefore no knowledge spillovers from multinational firms in China. As reported by Table 7, China's manufacturing GDP would decrease by 13.7% in this scenario, compared to the baseline. The impact of multinationals on China's real income is smaller (11.3%) than the impact on output, as the profits earned by multinationals would be remitted to their originating country. Overall, the magnitude of multinationals' contribution to China's growth is similar to that of several other important policies studied in the literature, including trade liberalization (Tombe and Zhu, 2019) or Hukou reform (Hao et al., 2020). Figure 4 plots proportional changes in China's yearly manufacturing output in the absence of multinationals. We find that the output loss was large in the early 2000s, which was mainly due to China's high reliance on transferred ideas from multinationals. As domestic innovation ("non-transferred ideas") soared especially after 2005, the impact of multinationals on China's manufacturing output became much smaller.[27]

[27]Another driver for the large output losses in the early 2000s is that in the absence of multinationals, domestic firms would make more innovation initially, as profits from innovation increased (which

Table 7: Effects of Multinationals on China's Output, Wages and Idea Stock

	Panel A: Proportional changes in counterfactual scenarios		
	(1)	(2)	(3)
	No MNE in China	No MNE spillovers	No Quid Pro Quo policy
	($\zeta_{CN,t} = 0$, $\phi_{CN} = 0$)	($\phi_{CN} = 0$)	($\eta_{CN} = 0$)
China's real output	-13.7%	0.0%	10.4%
China's real income	-11.3%	-0.2%	1.2%
China's real wage	-10.2%	-0.9%	7.1%
Idea stock owned by China	-27.3%	-4.8%	-37.3%
non-transferred	6.3%	-10.6%	-1.5%
transferred	-100%	9.2%	-100%
	Panel B: Decomposition of China's gains from MNEs (changes in real income)		
	Overall	Static	Dynamic
	11.3%	0.5%	10.8%

Notes: This table displays the effects averaged between 2000 and 2015.

Table 7 shows that without multinationals, China's total idea stock would drop by 27.3%, primarily due to the absence of knowledge transfers via the Quid Pro Quo policy. Interestingly, in this scenario, the idea stock produced by Chinese domestic firms ("non-transferred ideas") would increase by 6.3%. This indicates that the negative effects of heightened competition outweigh the positive effects of knowledge spillovers, resulting in the adverse net effects of multinationals on Chinese firms' idea stock.

In Panel B of Table 7, we conduct a decomposition of the gains in real income from multinationals into static (changes in prices and profits) and dynamic (changes in R&D and idea stock) components, in accordance with Proposition 1. Our findings show that, within the overall gains (11.3%), the static component accounts for a mere 0.5%. This minimal static gain stems from two opposing effects: while multinationals introduce more ideas to China, thereby reducing the self-absorption shares of domestic firms' production Π_{iiit} and boosting welfare, their entry also intensifies competition within China, leading to lower profits for domestic firms, and consequently reducing E_{it}/R_{it} and welfare. Conversely, the dynamic component makes the most significant contribution of 10.8%. This substantial dynamic gain stems from technology transfers that elevate China's idea stock, as well as knowledge spillovers that reduce the number of R&D workers needed to achieve the similar level of R&D output.

dominate the force of the lack of spillovers). Thus, there would be more R&D workers in the early 2000s, resulting in less production.

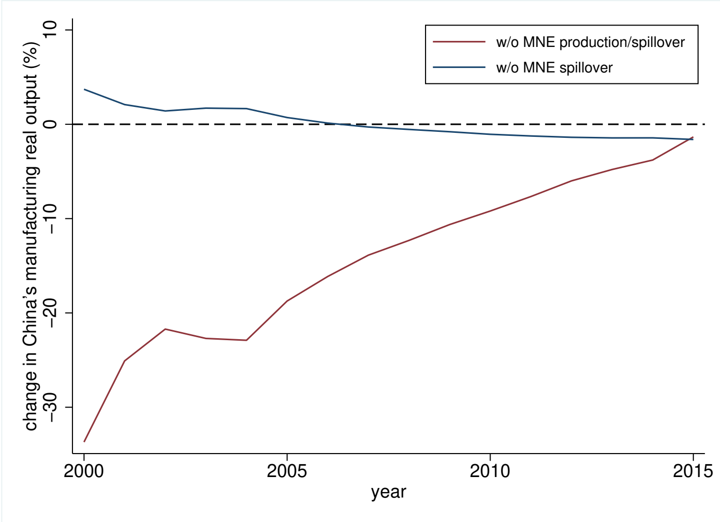
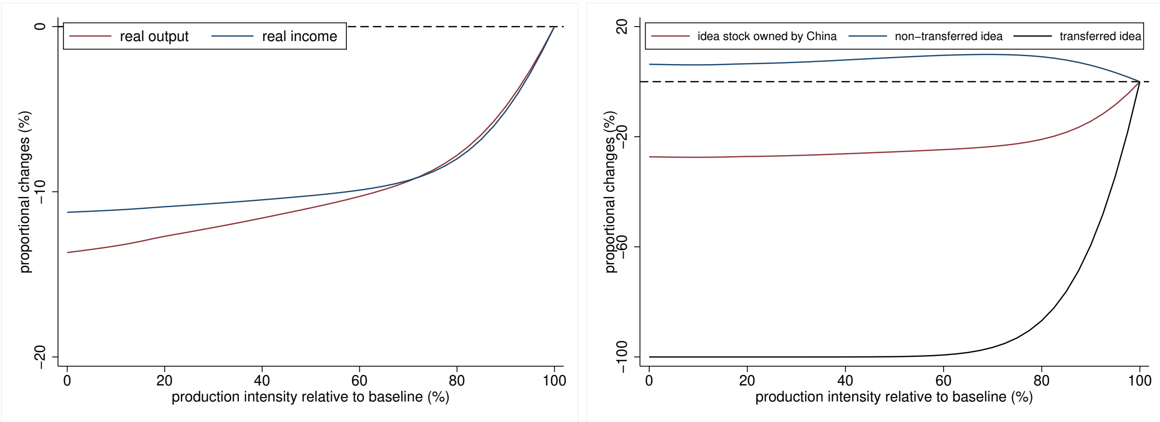


Figure 4: Output Changes in Counterfactual Scenarios, Relative to Baseline

To isolate the impact of multinationals' spillovers on domestic innovation, in Column (2) of Table 7, we shut down knowledge spillovers from multinationals. Our analysis reveals that in this counterfactual scenario, the idea stock generated by Chinese domestic firms would decrease by 10.6% compared to the baseline model, reaffirming the positive effects of multinationals on China's technology via knowledge spillovers.[28] While the average change in output is negligible between 2000 and 2015, Figure 4 shows that the absence of spillovers results in initially high manufacturing output (attributable to the reduced number of R&D workers), followed by a persistent decline, particularly in the late 2010s (by 2%), due to a lower accumulation of ideas.

Impact of Quid Pro Quo Policy. To evaluate the impact of the Quid Pro Quo policy on production and technology, we conduct a simulation wherein the Quid Pro Quo policy is absent ($\eta_{CN} = 0$). As illustrated in Column (3) of Table 7, in comparison to the baseline scenario, China's GDP would increase by an average of 10.4% over 2000-2015 in this alternative scenario, primarily driven by the heightened entry of multinationals. Nevertheless, due to the repatriation of profits by these multinationals back to their home countries, the increase in China's income is much more modest at 1.2%. Additionally, in the absence of technology transfers and amidst growing competition from multinationals, the idea stock owned by Chinese firms would decline by 37.3%.

[28]This impact is less pronounced than the targeted moment, primarily due to general equilibrium effects: the absence of spillovers results in decreased demand for R&D workers and a diminished idea stock, causing a decrease in the wage rate and an increase in the profits per idea.



(a) China's GDP

(b) China's Technology Capital Stock

Figure 5: Impact of Multinationals' Relocation from China

5.2 Departure of Multinationals from China

China has long been recognized as the "world factory" and an attractive location for foreign multinationals. However, recent years have seen a gradual shift of (especially labor-intensive) manufacturing from China to other emerging nations with comparative advantages in labor costs (Hanson, 2020). More critically, geopolitical issues and supply chain disruptions, including pandemics (Grossman, Helpman and Lhuillier, 2023; Freeman and Baldwin, 2020), have motivated multinational firms to swiftly diversify their supply chains and relocate away from China, avoiding "putting all the eggs in one basket" (Miroudot, 2020). Consequently, the number of inbound greenfield foreign investments in China has substantially declined, with investment levels in 2022 only half of what China received in 2019 (Barklie, 2023).

Our model considers the intensity of using ideas for multinationals in China, $q_{iCN,t}$, which is based on the tradeoff between higher profits from more intensive use of ideas and more technology losses due to Quid Pro Quo policy. However, we did not take into account other drivers of multinational firms' decision to locate their production in China, such as geopolitical issues and supply chain risk. To evaluate the quantitative effects of multinational firms' relocation from China, we exogenously adjust multinationals' intensity of using ideas in China, which is no longer based on the optimal choice. The goal of this exercise is to capture other influences that could alter multinational firms' willingness to locate their production in China.

Figures 5a and 5b demonstrate that a decrease in the intensity of multinational firms' adoption of ideas results in a downturn in both China's GDP and idea stock.

For example, if the intensity of multinational firms' utilization of idea stock in China is halved from the baseline, China's GDP is projected to drop by 11%, with the idea stock declining by 25.5%, primarily due to diminished technology transfers. Interestingly, we observe a hump-shaped effect on China's idea stock when multinational firms depart from the country: while a minor exodus may enhance domestic innovation by reducing market competition, a significant departure could largely counteract these benefits by decreasing knowledge spillovers.

While a precise assessment of the consequences of multinational firms' relocation from China necessitates the inclusion of other important factors into the model, our parsimonious model exercise indicates that the reluctance of foreign multinationals to invest in China could have substantial adverse effects on China's economy, particularly on its technology levels.

Impact of Multinationals' Departure from China on Other Economies. The departure of multinationals from China would inevitably affect other economies. In Table 8, we outline the effects on Asian and emerging economies when the utilization of idea stock by multinational firms in China is reduced by half compared to the baseline. As manufacturing relocates from China, there's a noticeable upsurge in these economies' GDP, especially for neighboring Asian economies, primarily fueled by heightened exports and multinational operations. Nonetheless, since sourcing from China becomes costlier, price indexes also climb, counterbalancing the output increase and resulting in relatively lower welfare levels in these economies.[29]

5.3 Subsidy on Multinationals

In developing nations, governments often invest significant resources to attract foreign multinational corporations. One of the primary motivations behind this strategy is to stimulate technology development of domestic firms (Amiti et al., 2023). Through the lens of our model, we highlight two positive externalities resulting from multinational corporations' technological decisions. Firstly, technology transfers from these corporations would augment China's intellectual capital. Secondly, knowledge spillovers would bolster the effectiveness of domestic innovation within China. These external-

[29]Korea experiences a notably significant decline in real income. This is primarily due to Korean multinational companies making substantial investments in China relative to Korea's GDP. Consequently, the departure of multinational firms from China results in a considerable reduction in profits for Korean multinational corporations.

Table 8: Impact of Multinationals' Departure from China

	MNEs' Intensity Halved in China				
	GDP	MNE's output	Export	Price index	Real Income
Brazil	0.81%	0.42%	0.51%	0.85%	-0.03%
India	0.87%	0.87%	0.60%	0.95%	-0.08%
Indonesia	0.85%	0.48%	0.44%	0.95%	-0.07%
Japan	1.06%	1.77%	0.12%	1.08%	-0.04%
Malaysia	0.89%	0.73%	0.45%	0.96%	-0.07%
Mexico	0.82%	0.34%	0.50%	0.86%	-0.03%
Philippines	0.92%	0.71%	0.48%	1.07%	-0.13%
Korea	0.98%	2.99%	1.97%	0.97%	-0.96%
Taiwan	1.08%	1.52%	0.24%	1.15%	-0.07%
Thailand	0.94%	0.33%	0.41%	1.02%	-0.08%
Viet Nam	0.96%	0.96%	0.37%	1.16%	-0.20%

Notes: This table displays the effects averaged between 2000 and 2015. We maintain the global GDP at the same level as in the baseline, following Dekle, Eaton and Kortum (2008).

ities imply that the current level of multinational operations may be below optimal, thus policies incentivizing multinational entry into China could prove beneficial.

We now analyze a subsidy on multinational production within China. Specifically, the government provides a subsidy, funded by lump-sum taxes, equivalent to a fraction $x \geqslant 0$ of the production expenses incurred by multinationals operating in China. We can interpret x as reflecting preferential access to production factors. For instance, in an effort to attract Tesla's gigafactory, the Shanghai government provided industrial land at a significantly discounted rate compared to prevailing market prices.[30]

Figure 6 reports the impact of varying subsidy rates (x) on the logarithm of China's real income, with the baseline value normalized to zero for comparative analysis. We find that subsidizing multinational corporations boosts China's income by fostering increased multinational participation, which also benefits domestic firms through positive externalities. However, higher subsidy rates entail greater financial costs for the Chinese government. Notably, China's real income (the sum of wage income and profits net of subsidy costs) exhibits a hump-shaped relationship with subsidy rates. At a subsidy rate of $x = 20\%$, we observe the most substantial increase (7.8%) in China's real income, resulting in an overall GDP increase of 11.3%.

[30]See https://www.yicaiglobal.com/news/tesla-buys-discounted-land-for-shanghai-gigafactory

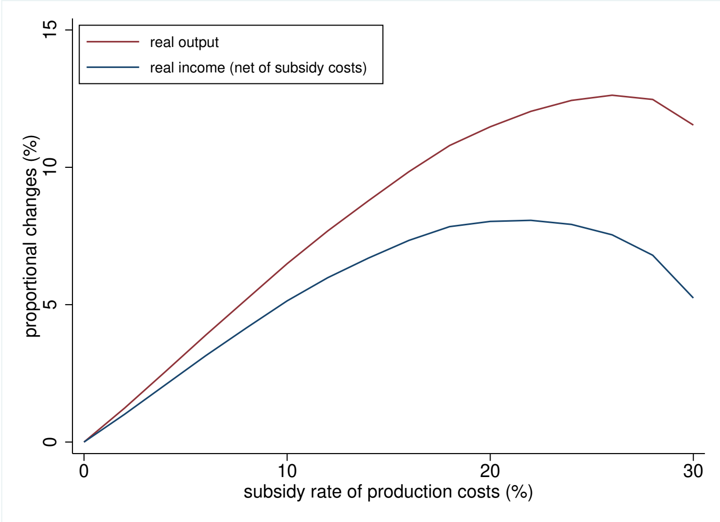


Figure 6: Subsidy on Production Costs of Multinationals in China

5.4 Robustness

In this subsection, we provide a series of robustness checks for our quantitative findings. Table 9 presents a summary of the results, which compares the main quantitative results across the baseline and alternate model specifications. Although the results may differ across scenarios, we consistently observe a significant impact of multinational activities on China's GDP and idea stock.

Considering Affiliate Innovation. In our baseline model, we only considered innovation by headquarters and abstracted from affiliate innovation. However, the recent literature (Bilir and Morales, 2020; Fan, 2023; Liu, 2024) and our evidence in Section 2 indicate nonnegligible innovation from multinational affiliates. To take affiliate innovation into consideration, we make two assumptions. First, we follow evidence in Bilir and Morales (2020) to consider the difference in geographical applicability between parents' and affiliates' innovation: unlike parents' innovation that can be applied globally, affiliates' innovation can only be applied to production in the host country.[31] Second, due to the lack of data, we only focus on multinational affiliates' innovation in China. We consider that affiliates' innovation production function is identical to that of their parent firms in equation (13) except for a multiplicative term $0 < \iota < 1$, capturing efficiency losses of multinational R&D in host countries.

[31] Bilir and Morales (2020) document that for US multinationals, there is a positive impact of parent innovation on affiliates' productivity, whereas conversely, affiliate innovation does not affect performance at other sites.

We calibrate ι to match the share of multinational affiliates' patents in all multinationals' patents in China, which is 23% according to Table 1. We recalibrate all other parameters to match the targeted moments listed in Table 6. Table 9 shows the impact of multinationals on China is very similar in this scenario compared to the baseline model. If anything, the impact of multinationals on China's GDP is slightly smaller than the baseline, as the entry of multinationals reduces the amount of production workers as multinational affiliates also hire R&D workers for innovation.

Using Quality-adjusted Patent Numbers. The number of patents may not accurately depict the gap in technology capital stock between China and other countries, especially given the widespread concerns about the low quality of Chinese patents. To address this issue, we adjust each country's patent numbers by patent quality index drawn from the OECD database (see Appendix D.5 for details on this patent quality measure). We then recalibrate the model parameters.

Panel B of Table 9 indicates that multinationals have a more substantial impact on China's GDP in the recalibrated model than in the baseline model. This is because, in the recalibrated model, as the quality of foreign patents is mostly higher than that of China's patents, China's idea stock relies more heavily on transferred ideas from multinationals. Therefore, when multinational firms exit China, China's idea stock experiences a more significant decline. China's growing dependence on transferred technology also reduces the employment of firms using non-transferred ideas, which intensifies competition effects and leads to a more significant negative impact of multinationals on Chinese firms' innovation activities.

Not Considering Patents Held by Joint Ventures as Technology Transfers. In our baseline calibration, we calculated the proportion of multinational knowledge transferred to China by assuming that all patents owned by joint ventures were transferred. However, given the uncertainty regarding whether all patents held by joint ventures are indeed transferred, we now only account for patent transactions and licenses as transfers. Consequently, the share of multinational technology transferred to China decreases significantly to 4% (compared to the baseline of 12%). All model parameters are then recalibrated to meet the revised data moments.

Panel C of Table 9 indicates that multinationals have a lower (but still considerable) impact on China's GDP in the recalibrated model than in the baseline model. This is because, in the recalibrated model, China relies less on transferred ideas due

Table 9: Impact of No Multinationals on China: Robustness Checks

Real GDP	Real income	Real wage	Idea stock owned by China: Overall	Non-transferred	Transferred
Baseline model					
-13.7%	-11.2%	-10.2%	-27.3%	6.3%	-100%
Panel A: Considering affiliate innovation					
-13.4%	-11.2%	-10.2%	-27.2%	6.6%	-100%
Panel B: Using quality-adjusted patent numbers					
-14.1%	-11.7%	-10.4%	-28.1%	7.1%	-100%
Panel C: Not considering joint ventures as technology transfers					
-8.8%	-7.1%	-6.2%	-16.4%	-0.9%	-100%
Panel D: Considering technology transfers and spillovers in other countries					
-14.1%	-11.6%	-10.7%	-28.9%	5.5%	-100%

to the lower share of multinationals' technology transferred to China. As a result, the competition effects for firms using non-transferred technology become smaller and similar in magnitude to the effects of knowledge spillovers, leading to a negligible impact of multinationals on Chinese firms' innovation activities.

Considering Technology Transfers and Spillovers in Other Countries. In our baseline calibration, we focused solely on technology transfers and spillovers within China due to data constraints. To address this limitation and ensure robustness, we adopt a methodology similar to Holmes, McGrattan and Prescott (2015), assuming that developing countries in our calibration implement the same Quid Pro Quo policy as China, whereas advanced economies do not implement such policy. Additionally, we assume that the strength of multinationals' spillovers on domestic innovation (ϕ_{ij}) in other countries mirrors that of China. Panel D of Table 9 reveals that the quantitative results in this alternative scenario closely resemble those of our baseline results.

6 Conclusion

Multinational activities transmit technologies between countries. Using comprehensive patent data from China, we document: (1) multinational affiliates and their foreign parent firms comprise a significant portion of patents filed with China's patent office; and (2) there are subsequent transfers and spillovers of these technologies to domestic firms. Guided by the empirical findings, we develop and quantify a tractable framework of multinational activities featuring cross-country technology flows, transfers, and spillovers. The calibrated model suggests that without multinational production and knowledge spillovers, China's idea stock would drop by 27%. The model also suggests that as a result of multinationals' technology transfers and spillovers, subsidizing multinational production in China would be socially beneficial.

This paper focuses on examining the contribution of multinational activities to conveying know-how as reflected through patent data. Arguably, technologies owned by multinationals may encompass a broader scope than what is reflected in patents (Alviarez, Cravino and Ramondo, 2023). Additionally, multinational activities have the potential to transmit knowledge through their employees (Setzler and Tintelnot, 2021). Exploring the quantitative significance of these alternative channels presents a promising avenue for future research, as it would contribute to a more comprehensive assessment of the impact of multinational activities on technologies in host countries.

References

Acemoglu, Daron, and Fabrizio Zilibotti. 2001. "Productivity Differences." *The Quarterly Journal of Economics*, 116(2): 563–606.

Acemoglu, Daron, Ufuk Akcigit, Nicholas Bloom, and William Kerr. 2018. "Innovation, Reallocation and Growth." *American Economic Review*, 108(11): 3450–91.

Adao, Rodrigo, Michal Kolesár, and Eduardo Morales. 2019. "Shift-share designs: Theory and inference." *The Quarterly Journal of Economics*, 134(4): 1949–2010.

Aitken, Brian J., and Ann E. Harrison. 1999. "Do Domestic Firms Benefit from Direct Foreign Investment? Evidence from Venezuela." *American Economic Review*, 89(3): 605–618.

Akcigit, Ufug, Murat A. Celik, and Jeremy Greenwood. 2016. "Buy, Keep or Sell: Economic Growth and the Market for Ideas." *Econometrica*, 84(3): 943–984.

Akcigit, Ufuk, and William R. Kerr. 2018. "Growth through Heterogeneous Innovations." *Journal of Political Economy*, 126(4): 1374–1443.

Alvarez, Fernando, and Jr Robert E Lucas. 2007. "General equilibrium analysis of the Eaton–Kortum model of international trade." *Journal of Monetary Economics*, 54(6): 1726–1768.

Alvarez, Fernando, Francisco Buera, and Robert Lucas. 2013. "Idea Flows, Economic Growth, and Trade." *NBER Working Paper*, 19667.

Alviarez, Vanessa. 2019. "Multinational Production and Comparative Advantage."

Journal of International Economics, 119: 1–54.

Alviarez, Vanessa, Javier Cravino, and Natalia Ramondo. 2023. "Firm-Embedded Productivity and Cross-Country Income Differences." *Journal of Political Economy*, forthcoming.

Amiti, Mary, Cédric Duprez, Jozef Konings, and John Van Reenen. 2023. "FDI and Superstar Spillovers: Evidence from Firm-to-Firm Transactions." *NBER Working Paper*, 31128.

Arkolakis, Costas, Natalia Ramondo, Andrés Rodríguez-Clare, and Stephen Yeaple. 2018. "Innovation and Production in the Global Economy." *American Economic Review*, 108(8): 2128–2173.

Bai, Jie, Panle Barwick, Shengmao Cao, and Shanjun Li. 2020. "Quid Pro Quo, Knowledge Spillover, and Industrial Quality Upgrading: Evidence from the Chinese Auto Industry." *NBER Working Paper 27644*.

Barklie, Glenn. 2023. "China's FDI Decline: Why are Foreign Companies Decreasing their Dependency on Asian Giant?" *Available at https://www.investmentmonitor.ai/insights/chinas-fdi-decline-foreign-companies-covid-geopolitics/.*

Bernard, Andrew B., Jonathan Eaton, J. Bradford Jensen, and Samuel Kortum. 2003. "Plants and Productivity in International Trade." *American Economic Review*, 93(4): 1268–1290.

Bilir, L. Kamran, and Eduardo Morales. 2020. "Innovation in the Global Firm." *Journal of Political Economy*, 128(4): 1566–1625.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen. 2013. "Identifying Technology Spillovers and Product Market Rivalry." *Econometrica*, 81(4): 1347–1393.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel. 2022. "Quasi-experimental Shift-share Research Designs." *The Review of Economic Studies*, 89(1): 181–213.

Brainard, S. Lael. 1997. "An Empirical Assessment of the Proximity-Concentration Trade-off Between Multinational Sales and Trade." *The American Economic Review*, 87(4): 520–544.

Brandt, Loren, and Kevin Lim. 2019. "Accounting for Chinese Exports." *Working Paper*.

Brandt, Loren, Johannes Van Biesebroeck, and Yifan Zhang. 2012. "Creative Accounting or Creative Destruction? Firm-level Productivity Growth in Chinese Manufacturing." *Journal of Development Economics*, 97(2): 339–351.

Brandt, Loren, Johannes Van Biesebroeck, Luhang Wang, and Yifan Zhang. 2017. "WTO Accession and Performance of Chinese Manufacturing Firms." *American Economic Review*, 107(9): 2784–2820.

Branstetter, Lee, and C. Fritz Foley. 2010. "Facts and Fallacies about U.S. FDI in China." In *China's Growing Role in World Trade*. 513–539.

Buera, Francisco J, and Ezra Oberfield. 2020. “The Global Diffusion of Ideas.” *Econometrica*, 88(1): 83–114.

Buera, Francisco, Joseph Kaboski, and Robert M. Townsend. 2021. “From Micro to Macro Development.” *NBER Working Paper*, 28423.

Buera, Francisco, Joseph Kaboski, and Shin Yongseok. 2021. “The Macroeconomics of Microfinance.” *Review of Economic Studies*, 88(1): 126–161.

Cai, Jie, Nan Li, and Ana Maria Santacreu. 2022. “Knowledge Diffusion, Trade, and Innovation across Countries and Sectors.” *American Economic Journal: Macroeconomics*, 14(1): 104–45.

Carlino, Gerald, and William R. Kerr. 2015. “Chapter 6 - Agglomeration and Innovation.” In *Handbook of Regional and Urban Economics*. Vol. 5 of *Handbook of Regional and Urban Economics*, , ed. Gilles Duranton, J. Vernon Henderson and William C. Strange, 349–404. Elsevier.

Chen, Heng, Bingjing Li, and Xiaodong Zhu. 2023. “Bottom-up Institutional Change and Growth: Theory and Evidence from China.” *Presentation Slides*.

Chen, Zhao, Zhikuo Liu, Juan Carlos Suarez Serrato, and Daniel Yi Xu. 2021. “Notching R&D Investment with Corporate Income Tax Cuts in China.” *American Economic Review*, 111(7): 2065–2100.

Coe, David T., and Elhanan Helpman. 1995. “International R&D spillovers.” *European Economic Review*, 39(5): 859–887.

Cohn, Jonathan B., Zack Liu, and Malcolm I. Wardlaw. 2022. “Count (and Count-like) Data in Finance.” *Journal of Financial Economics*, 146(2): 529–551.

Conte, M., P. Cotterlaz, and T. Mayer. 2022. “The CEPII Gravity database.” *CEPII Working Paper N°2022-05*.

Dekle, Robert, Jonathan Eaton, and Samuel Kortum. 2008. “Global Rebalancing with Gravity: Measuring the Burden of Adjustment.” *IMF Staff Papers*, 55(3): 511–40.

Deng, Jianpeng, Chong Liu, Zi Wang, and Yuan Zi. 2023. “Local Corporate Taxes and the Geography of Foreign Multinationals.” *Working Paper*.

Ding, Xuedong, and Jim Li. 2015. *Incentives for Innovation in China.* Routeledge.

Eaton, Jonathan, and Samuel Kortum. 1999. “International Technology Diffusion: Theory and Measurement.” *International Economic Review*, 40(3): 537–570.

Eaton, Jonathan, and Samuel Kortum. 2001. “Technology, Trade, and Growth: A Unified Framework.” *European Economic Review*, 45(4–6): 742–755.

Eaton, Jonathan, and Samuel Kortum. 2002. “Technology, geography, and trade.” *Econometrica*, 70(5): 1741–79.

Fan, Jingting. 2023. “Talent, Geography, and Offshore R&D.” *Review of Economic Studies*.

Feenstra, Robert, and John Romalis. 2014. "International Prices and Endogenous Quality." *The Quarterly Journal of Economics*, 129(2).

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review*, 105: 3150–3182.

Freeman, Rebecca, and Richard Baldwin. 2020. "Supply Chain Contagion Waves: Thinking Ahead on Manufacturing 'Contagion and Reinfection' from the COVID Concussion." *VoxEU.org*.

Garetto, Stefania, Lindsay Oldenski, and Natalia Ramondo. 2021. "Multinational Expansion in Time and Space." *NBER Working Paper*, 25804.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2020. "Bartik Instruments: What, When, Why, and How." *American Economic Review*, 110(8): 2586–2624.

Gollin, Douglas. 2002. "Getting Income Shares Right." *Journal of Political Economy*, 110(2): 458–474.

Grossman, Gene M., Elhanan Helpman, and Hugo Lhuillier. 2023. "Supply Chain Resilience: Should Policy Promote International Diversification or Reshoring?" *Journal of Political Economy*, forthcoming.

Hanson, Gordon H. 2020. "Who Will Fill China's Shoes? The Global Evolution of Labor-Intensive Manufacturing." *NBER Working Paper*, 28313.

Hao, Tongtong, Ruiqi Sun, Trevor Tombe, and Xiaodong Zhu. 2020. "The Effect of Migration Policy on Growth, Structural Change, and Regional Inequality in China." *Journal of Monetary Economics*, 113: 112–134.

Head, Keith, and Thierry Mayer. 2014. "Gravity equations: Workhorse, toolkit, and cookbook." *Handbook of International Economics*, 4: 131–95.

He, Z.-L., T.W. Tong, Y. Zhang, and W He. 2018. "A Database Linking Chinese Patents to China's Census Firms." *Nature Scientific Data*, 5.

Holmes, Thomas J., Ellen R. McGrattan, and Edward C. Prescott. 2015. "Quid Pro Quo: Technology Capital Transfers for Market Access in China." *The Review of Economic Studies*, 82(3): 1154—-1193.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics*, 124(4): 1403–1448.

Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value." *The American Economic Review*, 76(5): 984–1001.

Javorcik, Beata Smarzynska. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers Through Backward Linkages ." *American Economic Review*, 94(3): 605–627.

Jiang, Kun, Wolfgang Keller, Larry D. Qiu, and William Ridley. 2024. "Technology Transfer vs. External Technology Spillovers: Evidence from China." *NBER Working*

Paper 24455.

Jones, Charles, and Paul Romer. 2010. "The New Kaldor Facts: Ideas, Institutions, Population, and Human Capital." *American Economic Journal: Macroeconomics*, 2(1): 224–245.

Jones, Charles I. 2002. "Sources of U.S. Economic Growth in a World of Ideas." *American Economic Review*, 92(1): 220–239.

Keller, Wolfgang. 2021. "Knowledge Spillovers, Trade, and Foreign Direct Investment." *NBER Working Paper*, 28739.

Keller, Wolfgang, and Stephen Ross Yeaple. 2013. "The Gravity of Knowledge." *American Economic Review*, 103(4): 1414–44.

Keller, Wolfgang, and Stephen Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm-Level Evidence from the United States ." *The Review of Economics and Statistics*, 91(4): 821–831.

Klenow, Peter J, and Andrés Rodríguez-Clare. 2004. "Externalities and Growth." *NBER Working Paper*, 11009.

König, M., K. Storesletten, Z. Song, and F. Zilibotti. 2022. "From Imitation to Innovation: What is All that Chinese R&D Going." *Econometrica*, 90(4): 1615–1654.

Konings, Jozef. 2003. "The Effects of Foreign Direct Investment on Domestic Firms." *Economics of Transition and Institutional Change*, 9(3): 619–633.

Lanjouw, Jean O, and Mark Schankerman. 2004. "Patent Quality and Research Productivity: Measuring Innovation with Multiple Indicators." *The Economic Journal*, 114(495): 441–465.

Liu, Ernest, and Song Ma. 2023. "Innovation Networks and R&D Allocation." *NBER Working Paper*, 29607.

Liu, Jin. 2024. "Multinational Production and Innovation in Tandem." *Working Paper*.

Liu, Zhiqiang. 2008. "Foreign Direct Investment and Technology Spillovers: Theory and Evidence." *Journal of Development Economics*, 85(1–2): 176–193.

Lu, Yi, Zhigang Tao, and Lianming Zhu. 2017. "Identifying FDI Spillovers." *Journal of International Economics*, 107: 75–90.

Manova, Kalina, Shang-Jin Wei, and Zhiwei Zhang. 2015. "Firm Exports and Multinational Activity under Credit Constraints." *The Review of Economics and Statistics*, 97(3): 574–588.

Ma, Xiao. 2023. "College Expansion, Trade, and Innovation: Evidence from China." *Working Paper*.

Miroudot, Sébastien. 2020. "Resilience versus Robustness in Global Value Chains: Some Policy Implications." *VoxEU.org*.

Moretti, Enrico. 2021. "The Effect of High-Tech Clusters on the Productivity of Top Inventors." *American Economic Review*, 111(10): 3328–75.

Perla, Jesse, Christopher Tonetti, and Michael E Waugh. 2015. "Equilibrium Technology Diffusion, Trade, and Growth." *NBER Working Paper No. 20881*.

Ramondo, Natalia, and Andrés Rodríguez-Clare. 2013. "Trade, Multinational Production, and the Gains from Openness." *Journal of Political Economy*, 121(2): 273–322.

Ramondo, Natalia, Andrés Rodríguez-Clare, and Felix Tintelnot. 2015. "Multinational Production: Data and Stylized Facts." *American Economic Review*, 105(5): 530–36.

Romer, Paul M. 1990. "Endogenous Technological Change." *Journal of Political Economy*, 98(5): S71–S102.

Sampson, Thomas. 2016. "Dynamic Selection: An Idea Flows Theory of Entry, Trade and Growth." *Quarterly Journal of Economics*, 131(1): 315–380.

Schumpeter, Joseph A. 1942. *Capitalism, Socialism, and Democracy.* New York: Harper & Brothers.

Setzler, Bradley, and Felix Tintelnot. 2021. "The Effects of Foreign Multinationals on Workers and Firms in the United States." *The Quarterly Journal of Economics*, 136(3): 1943–1991.

Silva, J. M. C. Santos, and Silvana Tenreyro. 2006. "The Log of Gravity." *The Review of Economics and Statistics*, 88: 641–658.

Somale, Mariano. 2021. "Comparative Advantage in Innovation and Production." *American Economic Journal: Macroeconomics*, 13(3): 357–96.

Squicciarini, Mariagrazia, Hélène Dernis, and Chiara Criscuolo. 2013. "Measuring Patent Quality: Indicators of Technological and Economic Value." *OECD Science, Technology and Industry Working Papers*.

Tintelnot, Felix. 2017. "Global Production with Export Platforms." *Quarterly Journal of Economics*, 132(1): 157–209.

Tombe, Trevor, and Xiaodong Zhu. 2019. "Trade, Migration and Productivity: A Quantitative Analysis of China." *American Economic Review*, 109(5): 1843–72.

Wang, Jian, and Xiao Wang. 2015. "Benefits of Foreign Ownership: Evidence from Foreign Direct Investment in China." *Journal of International Economics*, 97(2): 325–338.

Waugh, Michael E. 2010. "International Trade and Income Differences." *American Economic Review*, 100(5): 2093–2124.

Webb, Michael, Nick Short, Nicholas Bloom, and Josh Lerner. 2018. "Some Facts of High-tech Patenting." *NBER Working Paper 24793*.

Wei, Shang-Jin, Zhuan Xie, and Xiaobo Zhang. 2017. "From "Made in China" to "Innovated in China": Necessity, Prospect, and Challenges." *The Journal of Economic*

Perspectives, 31(1).

Zuniga, Maria Pluvia, and Dominique Guellec. 2009. "Who Licenses Out Patents and Why?: Lessons from a Business Survey." *OECD Science, Technology and Industry Working Papers, No.2009/05*.

A Additional Tables and Figures

Table A.1: Top Source Regions of Multinational Affiliates between 2000 and 2015

Regions	Number of Firms	Share
Hong Kong	244,201	53.6%
Taiwan	42,859	9.4%
Japan	26,687	5.9%
Korea	26,461	5.8%
The United States	25,350	5.6%
British Virgin Islands	11,508	2.5%
Singapore	10,497	2.3%
Macau	6,131	1.3%
Canada	5,499	1.2%

Notes: We identify the source region of each multinational affiliate based on the origin of the foreign owner with the largest equity share. This table presents all the source regions that accounted for at least 1% of all multinational affiliates in China between 2000 and 2015.

Table A.2: Summary Statistics for ASM

	All Firms			Domestic Firms			Multinational Affiliates		
	Obs	Mean	Std	Obs	Mean	Std	Obs	Mean	Std
Sales (logs)	1,724,290	9.94	1.38	1,547,707	9.89	1.37	176,583	10.43	1.33
Capital (logs)	1,725,543	8.24	1.72	1,549,493	8.18	1.70	176,050	8.75	1.74
Employment	1,739,967	4.70	1.15	1,563,089	4.66	1.15	176,878	5.06	1.15
TFP (labor share=2/3, logs)	1,289,194	2.78	1.11	1,155,720	2.77	1.11	133,474	2.81	1.05
TFP (HK2009, logs)	1,282,703	6.00	1.68	1,149,594	5.97	1.69	133,109	6.26	1.57
Cumul. patents (own, arcsinh)	1,749,167	0.02	0.21	1,571,858	0.02	0.20	177,309	0.02	0.24
Cumul. patents (own, log1plus)	1,749,167	0.02	0.17	1,571,858	0.02	0.16	177,309	0.02	0.19
Cumul. patents (foreign parents, arcsinh)							177,309	0.08	0.64
Cumul. patents (foreign parents, log1plus)							177,309	0.07	0.56
Spillovers from MNE affiliates (arcsinh)				1,571,858	0.28	1.11			
Spillovers from MNE affiliates (log1plus)				1,571,858	0.23	0.96			
Spillovers from foreign parents (arcsinh)				1,571,858	0.47	1.81			
Spillovers from foreign parents (log1plus)				1,571,858	0.43	1.64			

Notes: The statistics are computed based on firm-year observations. Sales, capital, and employment are in terms of thousands of RMB. We construct firm-year-level TFP by taking the residual of a constant-returns-to-scale Cobb-Douglas production function of capital and labor, using firm-level data on value added, employment, and fixed capital stock. We consider two different measures for the labor share in the Cobb-Douglas function: (a) we set the labor share to be 2/3 as suggested by cross-country evidence (Gollin, 2002); and (b) we follow Hsieh and Klenow (2009) who consider different labor shares across industries and the monopolistic competition (this is our preferred measure). The details for the construction of TFP measures are provided in Appendix B.4. The measures regarding patents and spillovers are described in the main text in Section 2.

Table A.3: Association between Firm Sales and Patents

Dependent Variable	Firm sales		TFP (labor share=2/3)		TFP (HK2009)	
	(1)	(2)	(3)	(4)	(5)	(6)
Cumul. patents (own, arcsinh)			0.004	0.036*	0.046	0.053
			(0.020)	(0.021)	(0.032)	(0.031)
Cumul. patents (foreign parents, arcsinh)			0.031	0.052**	0.085**	0.077**
			(0.023)	(0.023)	(0.037)	(0.035)
Cumul. patents (own, log1plus)	0.116***	0.048***				
	(0.025)	(0.019)				
Cumul. patents (foreign parents, log1plus)	0.143***	0.087***				
	(0.026)	(0.020)				
Firm-level Controls	No	Yes	No	Yes	No	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Obs	166,592	165,785	123,540	123,540	123,205	123,205
R-squared	0.890	0.912	0.721	0.733	0.716	0.733

Notes: In this table, we replicate the results in Columns (3)–(4) of Table 2 using log1plus transformations of patent numbers or using TFP levels as the dependent variables. The dependent variables are in logs. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). We construct firm-year-level TFP by taking the residual of a constant-returns-to-scale Cobb-Douglas production function of capital and labor, using firm-level data on value added, employment, and fixed capital stock. We consider two different measures for the labor share in the Cobb-Douglas function: (a) we set the labor share to be 2/3 as suggested by cross-country evidence (Gollin, 2002); and (b) we follow Hsieh and Klenow (2009) who consider different labor shares across industries and the monopolistic competition (this is our preferred measure). The details for the construction of TFP measures are provided in Appendix B.4. Standard errors are clustered at the firm level in case that there may be autocorrelation of errors. Significance levels: 10% *, 5% **, and 1% ***.

Table A.4: Impact of Technology Spillovers on Domestic Firms' Technology

Dependent Variable	Number of patent applications			
	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)
Spillovers from MNE affiliates	0.034***	0.034***	0.007	0.285*
	(0.002)	(0.002)	(0.024)	(0.158)
Spillovers from foreign parents	0.041***	0.040***	0.284***	-0.531
	(0.005)	(0.005)	(0.075)	(0.387)
Firm-level Controls	No	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	1,372,973	1,353,054	1,353,054	1,353,054
R-squared	0.015	0.016	0.000	0.000
Instrument			ind shift	WTO
First-stage F			477.22	23.33

Notes: In this table, we present the results from regression (4). The dependent and independent variables are measured after log1plus transformation. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). In Columns (4), we also control for the firm's exposure to the industry-level determinants of the FDI policy changes as found by Lu, Tao and Zhu (2017) (see footnote 14 for details). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

Table A.5: Impact of Technology Spillovers on Domestic Firms' Technology

Dependent Variable	Firm sales				TFP (labor share=2/3)				TFP (HK2009)			
	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Spill. MNE affiliates	0.044***	0.020***	0.023	0.064	-0.004	0.017***	0.039	-0.014	0.013	0.019**	0.056	-0.024
	(0.004)	(0.004)	(0.031)	(0.132)	(0.005)	(0.005)	(0.038)	(0.047)	(0.009)	(0.009)	(0.039)	(0.082)
Spill. foreign parents	0.238***	0.152***	0.234**	0.065	0.068***	0.127***	0.145	0.249**	0.151***	0.161***	0.145	0.339*
	(0.012)	(0.011)	(0.103)	(0.340)	(0.014)	(0.013)	(0.117)	(0.120)	(0.025)	(0.020)	(0.136)	(0.206)
Firm-level Controls	No	Yes	Yes	Yes	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,352,455	1,342,346	1,342,346	1,385,256	962,120	962,101	962,101	962,101	959,205	956,317	956,317	956,317
R-squared	0.003	0.138	0.138	0.138	0.000	0.058	0.058	0.058	0.000	0.033	0.033	0.033
Instrument			ind	WTO			ind	WTO			ind	WTO
First-stage F			566.07	53.15			695.65	2470.72			692.62	2456.75

Notes: In this table, we replicate the regressions in Columns (1)–(4) of Table 4 with different dependent variables. The dependent variables are in logs, while the independent variables are measured post IHS transformation. The results are quantitatively if we apply log1plus transformation to the independent variables. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). We construct firm-year-level TFP by taking the residual of a constant-returns-to-scale Cobb-Douglas production function of capital and labor, using firm-level data on value added, employment, and fixed capital stock. We consider two different measures for the labor share in the Cobb-Douglas function: (a) we set the labor share to be 2/3 as suggested by cross-country evidence (Gollin, 2002); and (b) we follow Hsieh and Klenow (2009) who consider different labor shares across industries and the monopolistic competition (this is our preferred measure). The details for the construction of TFP measures are provided in Appendix B.4. Columns (3), (7), and (11) use the instrument constructed in equation (5) (we analogously construct the instrument for spillovers from foreign parent firms). Columns (4), (8), and (12) use the instrument constructed in equation (6) (we analogously construct the instrument for spillovers from foreign parent firms). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

Table A.6: Impact of Technology Spillovers on Domestic Firms' Innovation

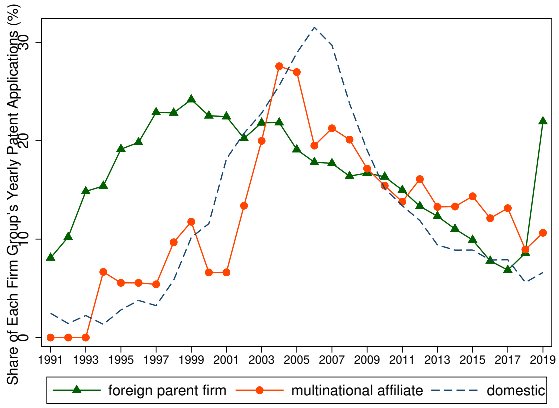
Dependent Variable	Number of parents			
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Spillover from both MNE affiliates	0.0010*	0.0010*	0.0016*	0.0010*
& foreign parents	(0.0006)	(0.0006)	(0.0008)	(0.0006)
Firm-level Controls	No	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	1,372,973	1,353,054	1,353,054	1,353,054
R-squared	0.001	0.002	0.001	0.002
Instrument			ind shift	WTO
First-stage F			2.2e+04	3.0e+04

Notes: In this table, we present the results from regression (4). The dependent and independent variables are in levels. The independent variable is constructed as $spillover_{it} = fdi\_spillover_{it} + par\_spillover_{it}$, which combines multinational affiliates' and their foreign parent firms' spillovers together. This aims to ease calibration in the quantitative analysis, in which we consider aggregate spillovers from both multinationals' knowledge brought into China and their knowledge created in China. The results are similar if we separately include spillovers from multinational affiliates and spillovers from their parent firms in the regressions. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.

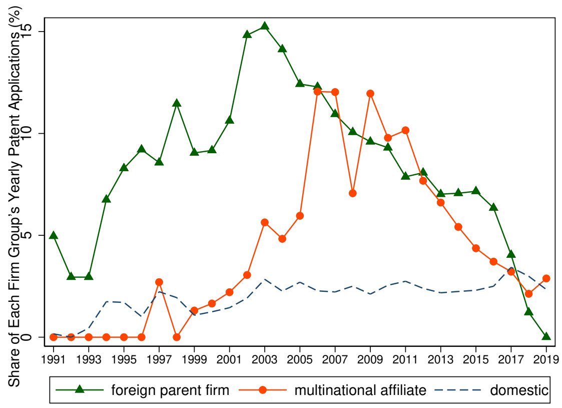
Table A.7: Impact of Technology Spillovers on Domestic Firms' Technology

Dependent Variable	Num of patent app		Innovation status		Firm sales		TFP (labor share=2/3)		TFP (HK2009)	
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
MNEs' share of industry sales	-0.010*	-0.024**	-0.006	-0.008	-0.391***	-0.387***	-0.443***	-0.451***	-0.620***	-0.634***
	(0.006)	(0.011)	(0.004)	(0.006)	(0.025)	(0.022)	(0.038)	(0.034)	(0.050)	(0.058)
Spillover from MNE affiliates	0.007	0.123***	0.035**	0.033**	0.054	-0.168	0.092***	-0.045	0.104**	-0.081
	(0.028)	(0.039)	(0.017)	(0.016)	(0.038)	(0.150)	(0.046)	(0.054)	(0.040)	(0.087)
Spillover from foreign parents	0.369***	0.392***	0.127**	0.218**	0.046	0.603	-0.166	0.290**	-0.219	0.424*
	(0.089)	(0.132)	(0.054)	(0.089)	(0.116)	(0.387)	(0.119)	(0.130)	(0.157)	(0.226)
Firm-level Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs	1,353,061	1,353,061	1,353,061	1,353,061	1,342,353	1,342,353	962,104	962,104	956,320	956,320
R-squared	0.000	0.000	0.000	0.000	0.139	0.137	0.057	0.057	0.032	0.032
Instrument	ind shift	WTO	ind shift	WTO	ind shift	WTO	ind shift	WTO	ind shift	WTO
First-stage F	469.04	234.85	469.04	234.85	471.63	46.56	558.36	2126.75	556.23	2116.27

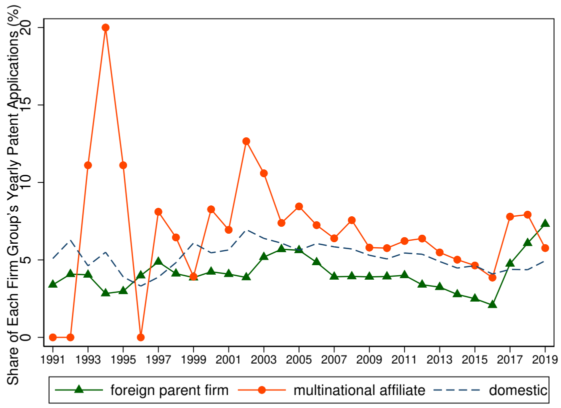
Notes: In this table, we replicate the regressions in Columns (3)–(4) of Table 4 with different dependent and independent variables. For the dependent variables, the number of patent applications is measured post IHS transformation, the innovation status is a dummy variable that equals 1 if patent applications are positive, whereas all other variables are measured in logs. For the independent variables, MNEs' share of industry sales represents the share of multinational affiliates' sales in total China's industry-level sales for firm i's affiliated industry in year t. Spillover effects are constructed according to equations (3) post IHS transformation. Firm-level controls include log fixed capital, log employment, and dummies of firms' registration types (e.g., private or state-owned firms). We construct firm-year-level TFP by taking the residual of a constant-returns-to-scale Cobb-Douglas production function of capital and labor, using firm-level data on value added, employment, and fixed capital stock. We consider two different measures for the labor share in the Cobb-Douglas function: (a) we set the labor share to be 2/3 as suggested by cross-country evidence (Gollin, 2002); and (b) we follow Hsieh and Klenow (2009) who consider different labor shares across industries and the monopolistic competition (this is our preferred measure). The details for the construction of TFP measures are provided in Appendix B.4. Columns with odd numbers employ the instrument created in equation (5) (we analogously construct the instrument for spillovers from foreign parent firms). Columns with even numbers use the instrument constructed in equation (6) (we analogously construct the instrument for spillovers from foreign parent firms). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are in parentheses and constructed by bootstrap over firms. Significance levels: 10% *, 5% **, and 1% ***.



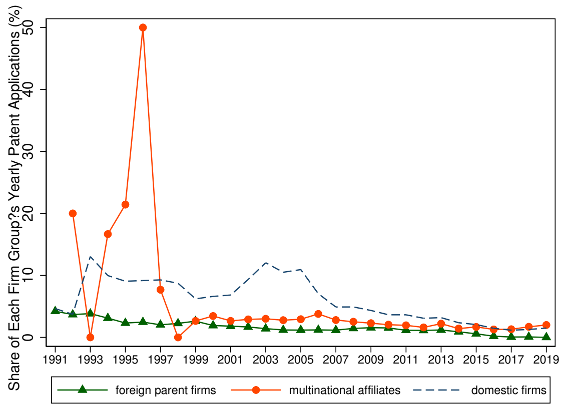
(a) Smart Phones



(b) Seminconductors

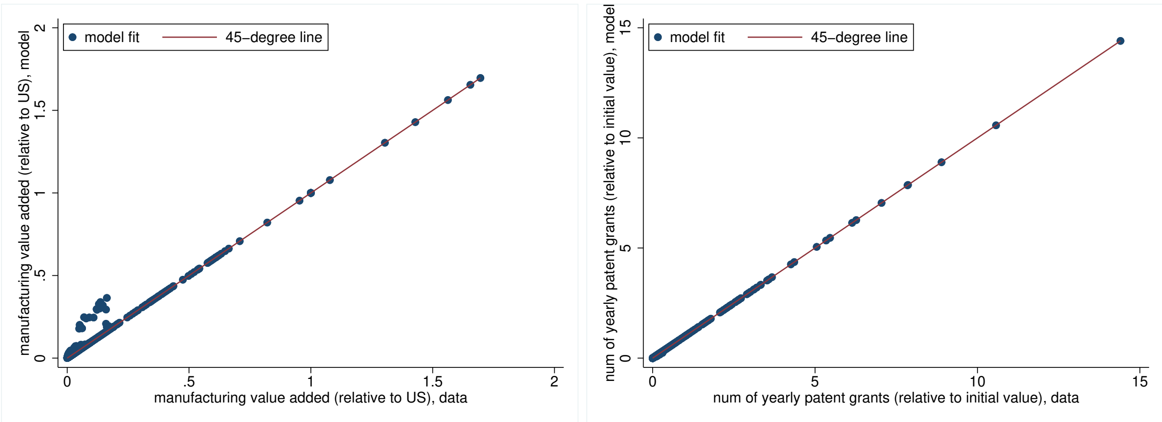


(c) Software



(d) Pharmaceuticals

Figure A.1: Time Trends for the Shares of High-tech Patents



(a) Region-Year Value Added

(b) Region-Year Innovation Intensity

Figure A.2: Comparison of Output and Innovation between Model and Data

B Additional Details of the Data

B.1 China's Registration Information of Industrial and Commercial Enterprises

The 2015 China Registration Information of Industrial and Commercial Enterprises encompasses all companies registered within China prior to 2015. Within this dataset, details are available for each registered firm, including the names and nationalities of their investors, along with information regarding their equity holdings.

To compile the sample of multinational affiliates for analysis, we initially select firms each of which has at least one non-mainland-China ("foreign") investor. Subsequently, we filter for firms where the combined equity ownership by foreign investors exceeds 30%. Finally, we consolidate the names of firms and investors according to the steps outlined in Appendix B.5.

B.2 Patent Application, Transaction, and License Data

Chinese patent application data is assembled by the China National Intellectual Property Administration (CNIPA). It covers detailed information on each patent applied to CNIPA, including the unique application number, application date, grant date, inventors, International Patent Classification (IPC) code, titles, and abstracts. China's patents are also classified into three types—design, invention, and utility models. Inventions are more related to innovative activities than the other two types. The data records the type of all patent applicants, namely firms (C), individuals (P), government (G), research institutions (R), university (U), and others (N).

To assemble the sample of patents for analysis, our focus lies on the following criteria: (1) invention patents, indicative of innovative endeavors; (2) patents applied for before 2015 and eventually granted;[32] and (3) patents applied for by firms. These latter two criteria are in line with our utilization of firm data preceding 2015.

CNIPA also provides data on patent transactions and licenses. This data provides information on the transfer of patented technology from one firm to another through licensing agreements or outright sales. The data on patent transactions and licenses includes information such as the patent's transaction/licensing date, the patent's application number, and the names of the firms involved in each transaction or license.

[32] Our emphasis on granted patents serves to alleviate concerns regarding the quality of patent applications.

In the case of a large corporate group, different subsidiaries may have different functions: some may focus on research and development, while others may primarily engage in production. In such scenarios, technology may be transferred or allocated within the corporate group, which is out of the scope of this paper. To address this data issue, we standardize firms' name and employ text analysis techniques to assess the similarity between the names of the two parties.[33] We exclude transactions and licenses where the names of the two parties are highly similar, as these are likely to be transactions and licenses between related firms.

Finally, to merge patent data with firm registration and financial data, we consolidate firm names according to the steps provided in Appendix B.5.

B.3 Technology Fields

This paper primarily relies on the IPC (International Patent Classification) technology field classification system, which was established by the Strasbourg Agreement in 1971. The IPC provides a hierarchical system of language-independent symbols for classifying patents and utility models according to their respective areas of technology. Since its inception, the IPC has undergone eight revisions. For the purposes of this paper, we mainly utilize 3-digit level IPC codes.

In this paper, we do not address any concordance issues when utilizing IPC classification, despite the possibility that patents in the CNIPA database may have IPC codes from different IPC versions. This is because at the 3-digit level of IPC codes, there have been minimal changes from version 1 to version 8. Below, we outline the altered classes between version 1 and version 8:[34]

- IPC1→IPC2: A01,A21-A24(d); B44 (r); C25 (+); E21(+).
- IPC2→IPC3: B09(+); B26(r); C02(r); C12(r); C30(+); E21(r); F16(r); G09(+).
- IPC3→IPC4: B25(r); B29(r); C23(r); G03(r).
- IPC4→IPC5: B67(r); B03(r); F25(r).
- IPC5→IPC6: B09(r).

[33]The standardization of firms' names involves the steps outlined in Appendix B.5 and further removing province/city names that appear in firms' names. To assess the similarity between firms' names, we utilize the Levenshtein distance and the Jaro–Winkler distance.

[34]In the items below, "(d)" denotes that this class is re-divided and given a new definition; "(r)" indicates a change in the definition of this class, which may include the addition of frontier concepts; "(+)" signifies the addition of this class; and "(-)" indicates the deletion of this class in the new version.

- IPC6→IPC7: B81(+).
- IPC7→IPC8 (2006.1): A21(r); A99(+); B99(+); C40(+); C99(+); D99(+); E99(+); F03(r); F99(+); G99(+); H99(+).
- IPC8 (2006.1)→IPC8 (2008.4): no changes.
- IPC8 (2008.4)→IPC8 (2009.1): A61-A63,A99(r).
- IPC8 (2009.1)→IPC8 (2010.1): A47(r).
- IPC8 (2010.1)→IPC8 (2014): no changes.
- IPC8 (2014)→IPC8 (2015): B31(r); B31(+).
- IPC8 (2015)→IPC8 (2016): no changes.

B.4 Annual Survey of Manufacturing

The Chinese Annual Survey of Manufacturing is an administrative dataset with detailed information on the demographics and balance sheets of manufacturing firms. On average, 200 to 400 thousand firms are surveyed in each sample year, representing more than 90% of China's manufacturing output. We use the data for the 2000–2007 period. This dataset provides detailed financial information such as firm names, value added, sales, employment, and capital stock, as well as 4-digit industry affiliation and registration types, for state-owned enterprises (SOEs) and large private firms with sales more than 5 million RMB.

Besides the variables directly provided by the data, we also construct two TFP measures:

- TFP (labor share = $2/3$): this measure is given by $\frac{Y_{it}}{K_{it}^{\alpha} {L_{it}}^{1-\alpha}}$, where Y_{it}, K_{it} and L_{it} capture the value added, book value of fixed capital, and employment, respectively, for each firm i operating in time t. The labor share $1-\alpha$ is given by $2/3$ following the evidence from Gollin (2002).
- TFP (HK2009): We use Hsieh and Klenow (2009)'s TFPQ measure given by $\frac{Y_{it}^{\frac{\sigma}{\sigma-1}}}{K_{it}^{\alpha_{s(i)}} {L_{it}}^{1-\alpha_{s(i)}}}$, where Y_{it}, K_{it} and L_{it} capture the value added, book value of fixed capital, and employment, respectively, for each firm i operating in industry $s(i)$ and time t. Here, we follow Hsieh and Klenow (2009) to consider monopolistic competition

across firms, with the elasticity of substitution between plants' value added σ being set to 3 (the exponent on Y_{it} is because value added Y_{it} includes effects of both prices and quantities under monopolistic competition). Because there are extensive labor distortions in China, we follow Hsieh and Klenow (2009) to proxy China's industry-level labor share $1 - \alpha_{s(i)}$ using the corresponding industry-level measure from the US.

Finally, we consolidate the names of firms according to the steps outlined in Appendix B.5.

B.5 Standardizing Firm Names

In this paper, we merge patent data, registration data, and firm financial data using firm names. To ensure accurate name matching, we implement a name matching method that involves standardizing firms' names, which is similar to the method employed in He et al. (2018). The specific steps for standardization are as follows:[35]

- Step 1: We standardize the firm's name by making the following adjustments: (1) we replace "gu fen you xian gong zi" and "you xian ze ren gong si" with "you xian gong si" in the firm's name; (2) we replace "chang you xian gong si" and "chang qi ye" with "chang" in the firm's name; and (3) we remove terms such as "dai qing li," "ge zhuan qi," "si ying zhuan he huo," and similar terms from the firm's name.
- Step 2: We convert all uppercase letters to lowercase and transform full-width characters into half-width characters.
- Step 3: We remove various special symbols from the data, such as "*", ">", etc.

C Additional Results of Quantitative Model

C.1 Balanced Growth Path

We assume that population L_{it}, iceberg costs τ_{ijkt}, productivity levels A_{ijt}, and innovation efficiency A^e_{it} remain time-invariant. We also assume that $\mu = 1$, which ensures endogenous growth (Romer, 1990; Eaton and Kortum, 2001). With these assumptions,

[35] We thank Dr. Xin Wang from Tsinghua for generously providing us with standardization codes.

we can now establish a balanced growth path for the model, wherein growth is derived from the accumulation of ideas. We consider that the knowledge stock grows at the constant rate g_T: $\frac{T_{ijt+1}}{T_{ijt}} = (1+g_T)$. We normalize the US's wage to 1, $W_{US} = 1$. Revenues, wages, and expenditures remain time-invariant on the balanced growth path. We now describe the conditions that characterize this balanced growth path.

First, according to equation (17), the intensity of ideas is determined by:

$$q_{ij} = \begin{cases} \min\left\{ \left(\frac{1}{\eta_j(\psi+1)}\right)^{1/\psi}, 1\right\} & \text{if } \eta_j > 0 \\ 1 & \text{if } \eta_j = 0, \end{cases} \tag{29}$$

which remains unchanged over time. On the balanced panel, we can solve the share of ideas brought to country j among all the ideas created in country i:

$$O_{ij} = \min\left\{ \left(\frac{(1-\eta_j q_{ij}^{\psi}) q_{ij} V_{ijt}}{f_t P_{it}}\right)^{\kappa}, 1\right\}, \tag{30}$$

To ensure that O_{ij} remains unchanged over time, we need $\frac{V_{ijt}}{f_t P_{it}} = \sum_{\tau=t}^{\infty} e^{-\rho(\tau-t)} \frac{1}{f_t P_{i\tau}} \frac{R_{ij\tau}}{T_{ij\tau}} \frac{1}{1+\theta}$ to be time-invariant, which holds if we assume that the fixed costs f_t grows at the rate $\frac{1-\theta}{\theta} g_T$, balancing the decline in profits due to the growth in knowledge stock.

The amount of workers in innovation L^e_{jt} and the utilization of q_{ijt} remains unchanged. With this, we can transform equation (14) as:

$$g_T = \frac{\Delta T_{ijt}}{T_{ijt}} = \begin{cases} A^e_{jt}\left(\sum_{i'} \phi_{i'j} \frac{T_{i'jt}}{T_{ijt}}\right)(L^e_j)^{\gamma} + \eta_j \sum_{i' \neq j} q_{i'j}^{\psi+1} O_{i'j} A^e_{i'} \left(\sum_k \phi_{ki'} \frac{T_{ki't}}{T_{ijt}}\right)(L^e_{i'})^{\gamma} & \text{if } i = j \\ (1-\eta_j q_{ij}^{\psi}) q_{ij} O_{ij} A^e_i \left(\sum_k \phi_{ki} \frac{T_{kit}}{T_{ijt}}\right)(L^e_i)^{\gamma} & \text{if } i \neq j \end{cases}$$

As knowledge ideas all grow at the same constant rate, their relative ratios do not change over time. Thus, we can use the first country's knowledge stock to normalize the knowledge stock for all countries $\mu_{ij} = \frac{T_{ijt}}{T_{11t}}$. Thus, the above equation can be rewritten as:

$$g_T = \begin{cases} A^e_{jt}\left(\sum_{i'} \phi_{i'j} \frac{\mu_{i'j}}{\mu_{ij}}\right)(L^e_j)^{\gamma} + \eta_j \sum_{i' \neq j} q_{i'j}^{\psi+1} O_{i'j} A^e_{i'} \left(\sum_k \phi_{ki'} \frac{\mu_{ki'}}{\mu_{ij}}\right)(L^e_{i'})^{\gamma} & \text{if } i = j \\ (1-\eta_j q_{ij}^{\psi}) q_{ij} O_{ij} A^e_i \left(\sum_k \phi_{ki} \frac{\mu_{ki}}{\mu_{ij}}\right)(L^e_i)^{\gamma} & \text{if } i \neq j \end{cases} \tag{31}$$

According to equation (20), the amount of researchers is determined by:

$$L_i^e = \left[\frac{\gamma A_i^e \left(\sum_j \phi_{ji} T_{jit}\right) \left(V_{iit} + \sum_{j \neq i} \left((1-\eta_j q_{ij}^{\psi}) q_{ij} O_{ij} V_{ijt} - \frac{\kappa O_{ij}^{(\kappa+1)/\kappa} f_t P_{it}}{\kappa+1} \right) \right)}{W_i} \right]^{\frac{1}{1-\gamma}}.$$

Rearranging this equation, we can obtain:

$$L_i^e = \left[\frac{\gamma A_i^e \left(\sum_j \phi_{ji} T_{jit}\right) f_t P_{it} \left(\frac{V_{iit}}{f_t P_{it}} + \sum_{j \neq i} \left((1-\eta_j q_{ij}^{\psi}) q_{ij} O_{ij} \frac{V_{ijt}}{f_t P_{it}} - \frac{\kappa O_{ij}^{(\kappa+1)/\kappa}}{\kappa+1} \right) \right)}{W_i} \right]^{\frac{1}{1-\gamma}}. \tag{32}$$

which is a constant given that $f_t P_{it}$ grows at the rate $-g_T$ and that $\frac{V_{ijt}}{f_t P_{it}}$ is constant.

Note that equation (31) is a system of N^2 equations, and equation (32) is a system of N equations. Given the wages and expenditures, we have 1 unknown g_T, (N^2-1) unknown μ_{ij} (notice that by normalization, $\mu_{11} = 1$), and N unknown L_i^e. Thus, we can solve g_T, μ_{ij}, and L_i^e from the system of equations (31)–(32). In our model, the uniform growth rate is facilitated by the global spillover effects of ideas (Klenow and Rodríguez-Clare, 2004).

We compute wages W_i and expenditures E_i by transforming equations (22) and (23) to the balanced path version:

$$\frac{(1+\theta)}{\theta} W_i (L_i - L_i^e) = \sum_j \sum_k \frac{\mu_{ji} (W_i \tau_{ik}/A_{ji})^{-\theta}}{\sum_{i',j'} \mu_{i'j'} (W_{j'} \tau_{j'k}/A_{i'j'})^{-\theta}} E_k, \tag{33}$$

$$E_k = W_k (L_k - L_k^e) + \frac{1}{1+\theta} \sum_j \sum_i \frac{\mu_{kj} (W_j \tau_{ji}/A_{kj})^{-\theta}}{\sum_{i',j'} \mu_{i'j'} (W_{j'} \tau_{j'i}/A_{i'j'})^{-\theta}} E_i. \tag{34}$$

Finally, according to equation (12), the price index grows at the rate $-\frac{g_T}{\theta}$. Therefore, real income grows at the rate of $\frac{g_T}{\theta}$.

C.2 Proof of Result 1

This result can be easily seen from the expression:

$$L_{it}^{e}=\left[\frac{\gamma A_{it}^{e}\left(\sum_{j}\phi_{ji}T_{jit}\right)^{\mu}\left(V_{iit}+\sum_{j\neq i}\left((1-\eta_{j}q_{ijt}^{\psi})q_{ijt}O_{ijt}V_{ijt}-\frac{\kappa O_{ijt}^{(\kappa+1)/\kappa}fP_{it}}{\kappa+1}\right)\right)}{W_{it}}\right]^{1/(1-\gamma)}, \tag{35}$$

which increases with ϕ_{ji} and V_{iit}, holding all else being constant. As g_{iit} increases with L_{it}^{e}, we can obtain the findings in Result 1.

C.3 Proof of Proposition 1

We note that the real income in country i can be expressed as:

$$W_{it}=\frac{E_{it}}{P_{it}}=\frac{E_{it}}{R_{it}}\frac{R_{it}}{P_{it}}=\frac{E_{it}}{R_{it}}\frac{\theta+1}{\theta}\frac{W_{it}L_{it}^{y}}{P_{it}}=\frac{E_{it}}{R_{it}}\frac{\theta+1}{\theta}\frac{(1-r_{it})L_{it}}{\gamma}\Pi_{iit}^{-1/\theta}T_{iit}^{1/\theta}A_{iit} \tag{36}$$

where the last equality uses the definition of trade share in equation (11) and price index in equation (12), as well as $r_{it}=1-L_{it}^{y}/L_{it}$. Evaluating equation (36) in the observed equilibrium and the model with only trade and taking the relative ratio, we can obtain the formula in Proposition 1 (note that productivity A_{iit} is exogenously given).

C.4 Gains from Openness

We consider the gains from openness, defined as the changes in real income as we move from a counterfactual equilibrium with no multinational production and no trade to the observed equilibrium. Evaluating equation (36) in the observed equilibrium and the model in autarky and taking the relative ratio, the gains from openness can be expressed as (note that in autarky $R_{it}=E_{it}$ and $\Pi_{iit}=1$):

$$GO_{it}=\underbrace{\left[(\Pi_{iiit})^{-1/\theta}E_{it}/R_{it}\right]}_{\text{static gains}}\underbrace{\left[\frac{1-r_{it}}{1-r_{it}^{AUT}}\left(\frac{T_{iit}}{T_{iit}^{AUT}}\right)^{1/\theta}\right]}_{\text{dynamic gains}} \tag{37}$$

where the superscript "AUT" denotes the variables in the autarkic economy with no trade and multinational production. Similar to the case of the gains from multinational production, the gains from openness include both static gains due to changes in real income (given the stock of ideas) and dynamic gains due to changes in innovation efforts and the stock of ideas.

D Additional Information for Quantitative Analysis

D.1 Countries and Regions

We consider the following 61 countries and regions: Argentina; Armenia; Australia; Austria; Azerbaijan; Belarus; Brazil; Bulgaria; Canada; Chile; China; China, Hong Kong SAR; Colombia; Czech Republic; Denmark; Egypt; Finland; France; Georgia; Germany; Greece; Hungary; India; Indonesia; Iran; Iraq; Israel; Italy; Japan; Kazakhstan; Latvia; Lithuania; Malaysia; Mexico; Mongolia; Morocco; Netherlands; New Zealand; Norway; Philippines; Poland; Portugal; Republic of Korea; Romania; Russian Federation; Singapore; Slovakia; Slovenia; South Africa; Spain; Sri Lanka; Sudan; Sweden; Switzerland; Taiwan; Thailand; Ukraine; United Kingdom; United States; Uzbekistan; and Viet Nam. We aggregate all the other countries not listed into a constructed rest of world.

D.2 Data Sources

In this subsection, we present supplementary data that we utilize to calibrate the model, in addition to the Chinese patent and firm data discussed in Section 2.

Manufacturing production and employment. We directly source data on manufacturing value added for the countries and regions under consideration from 2000 to 2015 from the World Bank. Additionally, we combine the World Bank's data on industrial employment share with employment data from the Penn World Table (Feenstra, Inklaar and Timmer, 2015) to derive manufacturing employment values for the same set of countries and regions during the specified time period.

Trade data. As we use the gravity equation in our calibration, we require international trade data between 2000 and 2015. We utilize the United Nations Comtrade Database with detailed information on bilateral trade flows. We follow the procedure in Feenstra and Romalis (2014) to clean this database to obtain bilateral trade flows between countries based on 4-digit SITC products. We then drop SITC products that belong to agriculture based on the WTO classification. Finally, we sum up product-level bilateral trade flows to derive aggregate bilateral trade flows between the countries and regions under consideration.

Geographic information is also essential for estimation of gravity equation. We obtain bilateral distances, contiguity, and GDP per capita data for each source-destination pair in each year between 2000 and 2015 from the CEPII database developed by Conte, Cotterlaz and Mayer (2022).

Patent data. We source the yearly number of patent grants, broken down by office and origin, for the period between 1985 and 2015, from the World Intellectual Property Organization (WIPO). Specifically, we rely on the data between 1985 and 1999 to build the knowledge stock for the initial year in our quantitative analysis, which is 2000. We rely on the data in later years to calibrate the innovation productivity.

Multinational production. We obtain the multinational affiliate sales by originating and host country between 1996 and 2001 from Ramondo, Rodríguez-Clare and Tintelnot (2015). We use this data to calibrate the productivity losses of bringing knowledge from the originating country to other host countries.

D.3 Construction of Data Moments

We now describe the construction of the data moments we targeted in the calibration.

Manufacturing value added in each country and year. We use data on manufacturing value added from the World Bank. For ease of comparison, we normalize manufacturing value added in each year by the US's level for that year (we perform the same normalization for the quantitative model).

Elasticity of multinational affiliate sales to distance between originating and host countries. Using data on multinational affiliate sales (aggregated over 1996–2001) from Ramondo, Rodríguez-Clare and Tintelnot (2015), we perform the following regression:

$$\log R_{ij} = \beta \log dist_{ij} + \mu_i + \iota_j + \epsilon_{ij}, \tag{38}$$

Table D.1: Elasticity of Multinationals' Revenue and Patent Flows to Distance

	$\log R_{ij}$	$\log T_{ij}$
$\log dist_{ij}$	-1.138***	-0.794***
	(0.098)	(0.021)
Origin FE	Yes	Yes
Destination FE	Yes	Yes
Obs	582	4,687
R-squared	0.846	0.831

where R_{ij} is the sales of multinational firms originating from country i and producing in j. β is the coefficient of interest, capturing the elasticity of multinational affiliate sales to distance between originating and host countries. μ_i and ι_j represent fixed effects for originating and host countries. Column (1) of Table D.1 reports that larger distance is associated with lower multinational affiliate sales. We use this coefficient as a targeted data moment and apply the same regression to the model-generated data to generate the model-predicted coefficient.[36]

Ratio of multinational affiliate sales to host country's production. We calculate the proportion of sales made by all multinational affiliates in each host country compared to the total production in that particular country. We then compute the mean of this ratio across all host countries, using their respective production values as weights. The data utilized is sourced from Ramondo, Rodríguez-Clare and Tintelnot (2015).

Ratio of multinational affiliate sales to China's total production in each year. To calculate the ratio of sales by all multinational affiliates to total manufacturing sales in China, we rely on the Annual Survey of Manufacturing. This ratio is computed for each year from 2000 to 2013. However, since data for 2014 and 2015 is unavailable, we interpolate the series to estimate the ratio for 2014 and 2015.

Number of granted patents in each country and year. We use the yearly number of domestic patent grants in each country from WIPO. For ease of explanation, we normalize these grants by the cumulative number of domestic patent grants in the initial year (2000). The initial year's count of patent grants is determined by aggregating all grants issued from 1985 to 1999.

[36]Since the initial year of our model is 2000, we utilize the 2000–2001 model-generated results to conduct the regression analysis, aligning with the time frame of the data sample employed.

Elasticity of number of granted patents to distance between originating and host countries. We use the number of patent grants before 2015, broken down by office and origin, from WIPO. Using the data, we perform the following regression:

$$\log T_{ij} = \beta \log dist_{ij} + \mu_i + \iota_j + \epsilon_{ij}, \tag{39}$$

where T_{ij} is the number of patent grants originating from country i and filed in country j. β is the coefficient of interest, capturing the elasticity of the number of granted patents to distance between originating and host countries. μ_i and ι_j represent fixed effects for originating and host countries. Column (2) of Table D.1 reports that larger distance is associated with a lower number of patents brought from country i to j. The coefficient on distance is smaller in magnitude compared to the elasticity of sales to distance shown in Column (1). This implies that while greater distance is linked to reduced idea flows, it also indicates lower productivity given the ideas that are exchanged.

Share of each country's granted patents being registered overseas. This share is determined by calculating the proportion of patent grants originating from a different country (compared to the patent office) to the total number of domestic patent grants. To accomplish this, we use the data from WIPO on the cumulative number of patent grants in 2015, which is further categorized by office and origin.

Fraction of multinationals' patents filed in China in terms of all patents filed in China. Using the findings from Section 2, we calculate the overall count of patent grants that are contributed by multinational affiliates and their foreign patents from 2000 to 2015. We then divide this total by the number of patent grants registered in China. It is important to note that apart from patent grants from both multinational and domestic firms, there are additional foreign patents filed with China's patent office. However, due to limited information on the utilization of these foreign patents in domestic production, we do not include them in our analysis.

Impact of multinationals' knowledge spillovers on China's patents. As it is difficult to interpret the regression results based on IHS and log1plus transformations, we rely on the coefficients in Appendix Table A.6, which are based on the levels of patent numbers and technology spillovers. We compute the number of patent applications in the counterfactual scenario of no spillovers by setting $spillover_{it} = 0$. We then aggregate the number of patent applications in the data and in the counterfactual scenario of no spillovers. Thus, we can obtain a proportional change in the number of China's patent applications if technology spillovers did not exist. As different regression specifications in Table A.6 report different coefficients, we take an average of the proportional changes computed by different regression specifications in Table A.6.

Share of multinationals' knowledge transferred to China. To compute the share of multinationals' knowledge transferred to China, we aggregate all patent transactions and licenses from multinational affiliates and their parent firms to Chinese domestic firms, and we also conservatively consider all patents held by joint ventures to be transferred to China. Combining information in Tables 1 and 3, our data suggests the fraction of multinationals' knowledge transferred to China is 11.5%. If we do not consider patents held by joint ventures, this fraction declines to 4.4%.

D.4 Solving Algorithm

In each period, our model resembles a static trade model akin to Bernard et al. (2003), whereas we also embed "dynamics" into the model through the evolution of idea stock. We now discuss how we solve the model numerically.

1. Given the sequences of wages, prices, and profits per idea $\{W_{it}, P_{it}, \bar{R}_{ij\tau}\}$ computed in Step 1, we can compute the value of an idea is:

   $$V_{ijt} = \sum_{\tau=t+1}^{\infty} e^{-\rho(\tau-t)} \frac{P_{it}}{P_{i\tau}} \bar{R}_{ij\tau}.$$

   While we carry out the model simulation until 2015, the value of an idea relies on profits beyond that year, which requires us to make certain assumptions. Therefore, for all periods after 2015, we assume that $P_{it} = P_{i,2015}$ and $\bar{R}_{ij\tau} = \bar{R}_{ij,2015} e^{-g_j(\tau-2015)}$, where g_j represents the growth rate of the idea stock between 2000 and 2015 for ideas available in the host country j, reflecting the fact that a higher growth rate of the idea stock diminishes profits per idea.[37]

   After obtaining the value of an idea, we can use equation (18) to compute the intensity of using ideas q_{ijt}, equation (19) to compute the share of ideas brought to country j among all the ideas created in country i O_{ijt}, and equation (20) to

[37] Our quantitative results are robust if we assume that profits per idea remain unchanged in all future periods, $g_j = 0$.

compute the amount of R&D workers L^e_{it}. Combining these results with the idea stock in the initial period $\mathbb{T}_1$,[38] we can compute the value of knowledge stock vector $\mathbb{T}_t$ through equation (14).

2. Given knowledge stock vector $\mathbb{T}_t$ and the amount of R&D workers L^e_{it} in each year t, we follow the iterative approach in Alvarez and Lucas (2007) to solve the equilibrium wages $\{W_{it}\}$ from good-market clearing condition in equation (22). We can then obtain trade shares Π_{ijkt}, aggregate price P_{it}, and expenditures E_{kt} from equations (11), (12), and (23). We can then obtain profits per unit of idea stock:
$$\bar{R}_{ij\tau} = \frac{\sum_k \Pi_{ijk\tau} E_{k\tau}}{T_{ij\tau}} \frac{1}{1+\theta}.$$

3. We update the wages, prices, and profits used in Step 1 through a weighted average of the previous values and the newly computed values in Step 2. We iterate on these values until the convergence of wages, prices, and profits.

D.5 Adjusting Patent Quality

We rely on Patent Quality Index (PQI) provided by the OECD Database. This index comprehensively includes several frequently utilized factors for evaluating patent quality, such as forward citation, family size, and the number of claims (Squicciarini, Dernis and Criscuolo, 2013). The OECD Database offers two composite indices for patent quality—patent quality index 4 and 6—based on Lanjouw and Schankerman (2004). PQI 4 consists of four components: the number of forward citations (up to 5 years after publication), patent family size, the number of claims, and the patent generality index. PQI 6 includes the same components as index 4, along with the number of backward citations and the grant lag index. The OECD PQI constructs these two indices for all European Patent Office (EPO) patents, and as EPO accepts patents from most countries, the OECD PQI employs the mean values of quality indices of these countries to facilitate comparisons of patent quality across nations (Squicciarini, Dernis and Criscuolo, 2013).

[38] The initial-year number of ideas in the originating country T_{ii1} is directly drawn from the data, and we compute the initial-year number of ideas brought from country i to $j \neq i$: $T_{ij1} = T_{i1} O_{ij1}$.

Table D.2: Patent Quality Measure

	China	The US	The ROW
OECD Patent Quality Index 4	0.87	1.09	1.00
OECD Patent Quality Index 6	0.97	1.03	1.00

The first and second rows in Table D.2 display the average patent quality for China and the ROW (all countries other than China), respectively, and we also display the results for the US. Clearly, we observe that the patent quality in China was inferior to that of the ROW and considerably lower than that of the leading innovating country, the US. This pattern is confirmed by Figure D.1 which illustrates the annual levels of patent quality for China, the US, and the ROW between 2000 and 2015. If anything, there is a slight increase in China's patent quality over time.

A natural concern regarding this data is the selection bias, as companies outside the European Union may face significant costs when applying for patents in the EPO. Consequently, they are more likely to apply only for high-quality and profitable patents. While it is difficult to control for this selection bias without making additional assumptions, we conservatively use PQI 4 averaged between 2000–2015 to measure quality of patents across countries, as PQI 4 suggests a lower patent quality for China's patents than PQI 6.[39]

[39] Alternatively, we also experimented with using the quality difference between China's and the US's applications to EPO as a measure of the quality difference between China and other countries. This is because both China and the US are geographically distant from the EU and have a substantial number of inventions. Furthermore, since the US is the world's leading innovator, comparing the quality between China and the US provides a conservative evaluation of China's relative patent quality. We find that our quantitative results are robust to this alternative way of measuring China's patent quality.

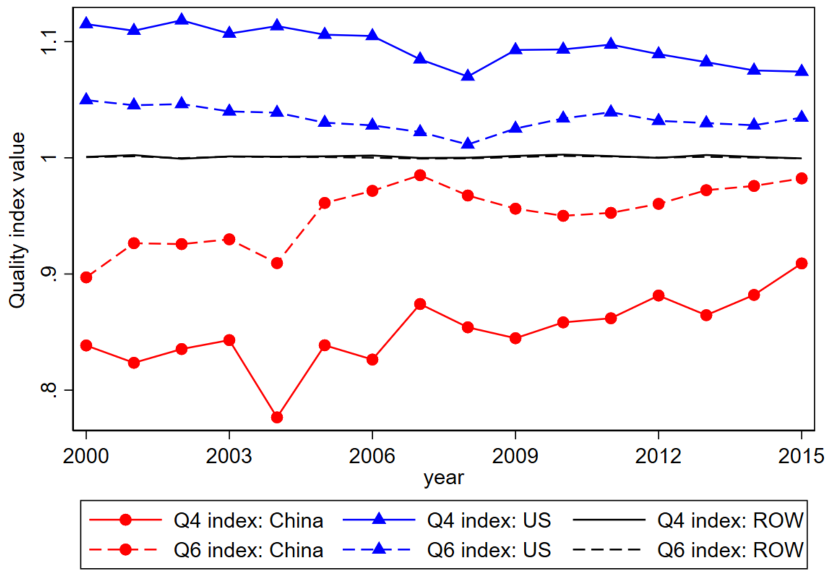


Figure D.1: Patent Quality Comparison