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

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Abstract

Multinationals play a crucial role in international knowledge diffusion. Given the recent concern that multinationals are departing China, understanding the importance of multinationals for China's technology is also particularly policy-relevant. 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 a quantitative framework of multinational activities featuring cross-country technology flows, transfers, and spillovers. Quantitatively, we find that without multinational production and knowledge spillovers, China's total technology capital would drop by 36%. Furthermore, due to the externalities of multinationals' technology investments, subsidizing multinationals in China will be socially beneficial, and reduced knowledge transfers/spillovers largely amplify the negative effects of multinationals' departing China on both China's GDP and technology.

Key Words: multinational activities; technology transfers; knowledge spillovers

JEL Codes: F23; O33

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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). The key feature of multinationals is that they bring know-how across borders and thus increase international idea flows. A large body of research has already studied how multinational activities bring production technology to other nations (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 (Holmes, McGrattan and Prescott, 2015; Amiti et al., 2023). These studies mostly 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). By 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 4% and 17% of all patent applications filed with China's patent office, respec-

[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.

tively. More intriguingly, we observe that patents owned by multinational affiliates were mainly innovated within 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 that technologies brought by parent firms were also integrated into the production processes of their affiliates.

Secondly, we explore technology transfers and spillovers from multinationals to domestic firms. Direct technology transfers (patent transactions and licenses) to domestic firms accounted for 3.5% 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, the average amount of citations received from domestic patents was 0.36 for patents held by multinational affiliates and their parent investors, smaller than the average among all patents (0.69). As citations may imperfectly capture knowledge 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.

Motivated by our empirical evidence, we proceed to develop a model to quantitatively understand the aggregate effects of multinational activities on China's technologies. We build on the pioneering work by Holmes, McGrattan and Prescott (2015) (HMP hereafter). In their framework, multinationals originating from each country make decisions regarding the amount of technology capital they bring to affiliates in other countries, while potentially encountering "Quid Pro Quo" policies in host nations that necessitate transfers of technology capital to domestic firms. Guided by our empirical findings, we introduce two key modifications to this framework. Firstly, given that a share of multinational affiliates' innovation takes place in China, we permit multinational affiliates to accumulate technology specific to the host country's market. This reflects that multinationals can generate new knowledge and technologies that cater to the local market, aligning with the evidence in Bilir and Morales (2020). Secondly, since multinational firms produce positive spillover impacts on domestic firms, we integrate knowledge spillovers into the production function of new technology. This allows us to capture the extent to which knowledge accumulated by one firm can spill over and benefit other firms in the same country.

Through the lens of our model, we show analytically that multinational activities can have both positive and negative effects on the innovation activities of domestic firms in host countries. On the one hand, multinational firms bring new technologies to the domestic market, which can reduce the marginal costs of accumulating new technology via spillover effects and lead to increased innovation activities. On the other hand, multinational entry can lead to intensified competition and thus reduce the marginal benefits for domestic firms to engage in innovation activities, reflecting the so-called Schumpeterian effect which suggests that larger profits incentivize innovation (Schumpeter, 1942). The net effect of multinational entry on domestic innovation will depend on the balance between these two opposing forces.

We calibrate our model to data from two countries, China and the Rest of the World, using the simulated method of moments. We focus on the steady state of the model, using production and patent data averaged between 2000–2015 to compute the data moments. Our calibrated model can match the targeted data moments very well.

Using the calibrated model, we quantify the impact of multinational activities on China's technology. First, we simulate a counterfactual scenario without multinationals' production and knowledge spillovers in China. We find that China's total technology capital would drop by 36.2% (GDP would decline by 6.4%) from the baseline equilibrium. This decline is primarily due to the absence of knowledge transfers via the Quid Pro Quo policy. Interestingly, in this counterfactual scenario, the technology capital generated by Chinese domestic firms would increase by approximately 13.2%, 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). To isolate the impact of knowledge spillovers, we perform the second exercise of only shutting down multinationals' knowledge spillovers. In this scenario, the technology capital generated by Chinese domestic firms would decrease by 21.1% compared to the baseline equilibrium, reaffirming the positive effects of multinationals on China's technology via knowledge spillovers.

We also perform three sets of additional analyses. First, we look into the impact of the Quid Pro Quo policy. We show that shutting down the Quid Pro Quo policy would reduce China's GDP and technology capital by 2.9% and 27.3%, respectively, due to the lack of technology transfers. The Quid Pro Quo policy has a hump-shaped effect on the significance of knowledge spillovers in shaping China's domestic innovation, as the degree of technology transfers affects both China's reliance on domestic innovation and multinationals' willingness to bring technology into China. Second, we find that subsidizing multinational production or innovation in China would improve China's GDP (net of subsidy costs), due to the externalities of multinationals' technology choices via technology transfers and spillovers.

Third, given the recent slump in China's FDI inflows (Barklie, 2023), largely due to concerns of supply chain diversification (Freeman and Baldwin, 2020; Grossman, Helpman and Lhuillier, 2023), we use our model to evaluate the effects of multinational firms' relocation from China. We find that if multinationals' intensity of using technology capital in China is reduced by half from the baseline, China's GDP would decrease by 4.9%, with only 23% of this reduction attributable to the decrease in multinational firms' production. The large amplification effects are mainly driven by the reduction in technology transfers resulting from the lower intensity of using technology capital of multinational firms, which reduces the technology capital stock available in China. This last result 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.

Finally, we perform several robustness checks of our model, including exploring different measures of technology capital, examining various approaches to measuring the Quid Pro Quo policy, and investigating how different innovation function settings impact the outcomes. We show that our results are robust across these different model specifications.

This paper is related to several stands of the literature. Our focus on knowledge transfers and spillovers connects us to a vast literature on international knowledge diffusion. Many studies have examined the effects of international knowledge diffusion (e.g., Coe and Helpman, 1995; Eaton and Kortum, 1999; Buera and Oberfield, 2020; Hsieh, Klenow and Nath, 2023), as reviewed by Keller (2021). Foreign investment can play a crucial role in international knowledge diffusion, as shown by the literature (e.g., Aitken and Harrison, 1999; Konings, 2003; Javorcik, 2004; Keller and Yeaple, 2009). While these prior studies mainly focused on the productivity impact of foreign firms' knowledge spillovers, we focus on their impact on innovative activities. Our use 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), fewer studies have quantitatively analyzed its impact (e.g., HMP, Brandt and Lim, 2019; Deng et al., 2023). Our paper is mostly related to HMP. Whereas we build on the framework developed by HMP, our paper differs from HMP in two aspects. Firstly, instead of calibrating the strength of technology transfers to match FDI flows and GDP, we use patent data to directly measure technology transfers, following the extensive literature that employs patents as a measure of technology, including Akcigit, Celik and Greenwood (2016), who use patent transactions to study technology transfers. This approach provides a more precise measurement of technology transfers, which is crucial for accurately quantifying multinationals' impact on China's technology and GDP.[3] Secondly, while HMP only focus on the impact of the Quid Pro Quo policy, our empirical analysis reveals significant knowledge spillovers from multinationals to Chinese firms. We utilize this evidence to discipline the strength of knowledge spillovers in the model and demonstrate that it amplifies the impact of multinationals on China's technology.

Finally, this paper makes contact with studies on China's innovation from a *macro perspective*.[4] 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)

[3]By using data on patent transactions and licenses, our paper is also related to recent studies (Choi and Shim, 2023; Santacreu, 2023) that use license or adoption data to directly measure cross-country technology transfers.

[4]There are also empirical studies on China's innovation (e.g., Hu and Jefferson, 2009; Jia and Ma, 2017).

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. Ma (2023) quantitatively explores the impact of college expansion on China's innovation. This paper complements these studies by focusing on the role of foreign investment in affecting 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 and present several robustness checks on our baseline results in Section 6. Finally, we conclude in Section 7.

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 foreign investors as *multinational affiliates* and extract the name and nationality information of these firms' investors. In total, we identify 276,104 multinational affiliates that were registered in China up until 2015. To determine the foreign status of these firms' investors, we consider investors as foreign if they originated from regions outside mainland China or Hong Kong. We exclude Hong Kong from our analysis, since many Chinese entrepreneurs also register firms in Hong Kong due to its well-developed financial markets and geographic proximity. On average, foreign owners hold 70% 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 Taiwan, Korea, the United States, and Japan, with each of these source regions accounting for over 10% 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).[5] By combining the ASM data with our dataset on multinational firms, we are able to investigate the impact of multinational firms on manufacturing innovation and production in China.

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, and inventors. We focus on all invention applications that were applied by firms between 2000–2015 and eventually granted,[6] which added up to 2,289,713 patents.

To gain a deeper understanding of technology transfers in China, we also 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 that occur between firms with similar names, which aims to avoid technology transfers within company groups. Finally, we obtain the data on patent citations, which provides detailed information on citing patents and cited patents for each citation that occurred. This citation data can be useful for providing insights into the impact of patented technology on subsequent innovation activities. This citation data contains information on the citing patent and the cited patent for each citation record.

[5]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.

[6]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.

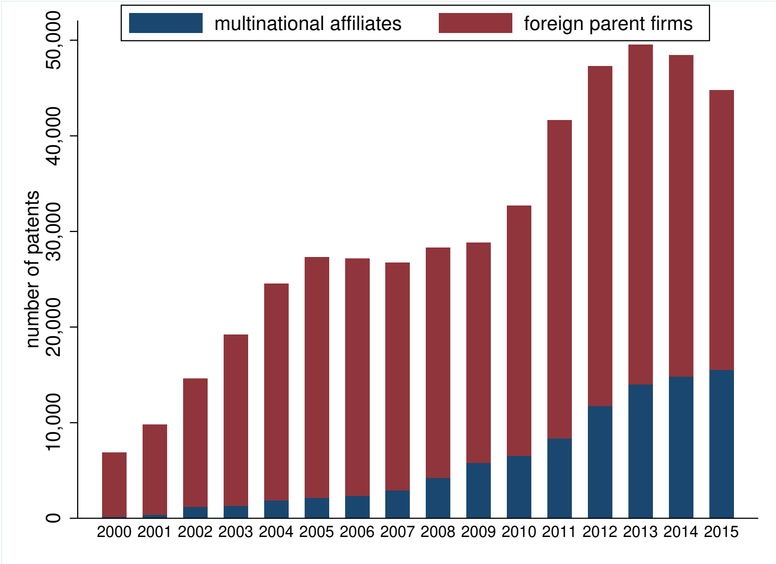


Figure 1: Number of Patents Applied by Multinational Affiliates and Foreign Parent Firms

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 consolidating firm names according to the procedure in He et al. (2018).

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 a relatively small number of 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 15,000 patents annually in China. In comparison, foreign parent firms applied for a higher number of patents in the early 2000s, with around 10,000 patent applications annually. However, the growth in the number of foreign parent firms' patent applications was less dramatic than that of affiliates' applications in the later years.

In Table 1, we provide 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 93,328 and 384,444 patents, accounting for 4.1% and 16.8% 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. Even though some of multinationals' technologies used in China may not be registered in China's patent office, the existing percentage already demonstrates a substantial contribution of multinationals to China's technology landscape. In Appendix Table A.2, we present the distribution of patent holdings across multinational affiliates and their foreign parent firms: consistent with the literature (e.g., Klette and Kortum, 2004), patenting activities were highly skewed, and a considerable portion of firms reported zero patents.

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 1% of multinational affiliates' patents have a foreign address, and that 96% 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): 10% of multinational affiliates' patents were first applied overseas, whereas 92% 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). Thus, in the quantitative model, we will model multinationals' innovation in both the headquarters and host countries.

To understand whether multinational affiliates and their foreign parent firms bring advanced technologies into China, we follow Webb et al. (2018) to determine whether each patent belongs to 10 advanced technologies (e.g., software, smart phones, drones) based on patents' titles and abstracts. As shown by Figure 2b, 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 30% of all the patents brought by foreign parent firms into China in

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

	Amount	% Foreign Address	% Foreign Priority Rights
Multinational Affiliates:	93,328	1.2%	10.3%
Joint Ventures	50,594	1.1%	10.1%
Foreign Parent firms	384,444	95.5%	91.9%

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

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.

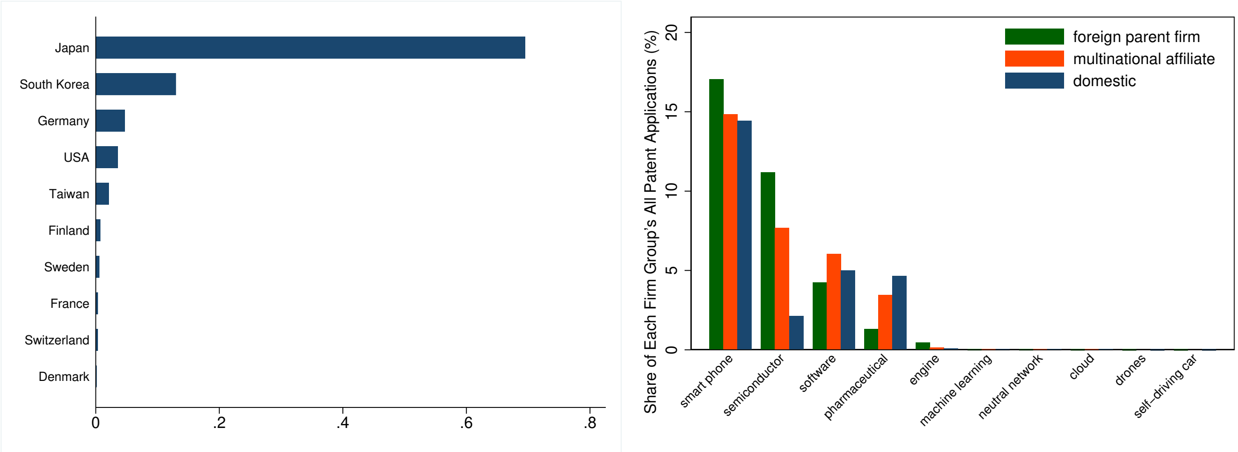
Given that foreign parent firms' patents were mostly brought from overseas, one may wonder whether they were actually applied to China's patent office for royalty allowance and not directly used in production. To explore this, we now provide suggestive evidence. Specifically, we perform the following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

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

The dependent variable $y_{i,t}$ is firm sales (in logs). For independent variables, $cumul\_patent_{i,t}$ is the cumulative amount of firm i's patent applications up to year t, and $cumul\_patent\_par_{i,t}$ is the cumulative amount of firm i's foreign parent firms' patent applications up to year t. $\mathbf{X}_{i,t}$ corresponds to the vector of firm-level controls. We also control for firm fixed effects μ_i and industry-year fixed effects $\gamma_{s(i),t}$, where we divide firms into the finest 4-digit industries, and $s(i)$ corresponds to firm i's affiliated industry. We combine the patent data and the firm-level data to perform this regression for manufacturing firms in 2000–2007. Appendix Table A.3 presents the summary statistics for this data.[7]

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 fixed effects and industry-year fixed effects. Columns (2)–(4) report the results for multinational affiliates

[7]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

under different specifications, where we include the cumulative amount of foreign parent firms' patent applications in Column (3) and add firm-level controls (capital, employment and ownership) in Column (4). We find that both the cumulative amount of firm i's own patent applications and that of its foreign parent firms' patent applications are positively associated with firm sales, and the coefficients are similar in magnitude. Although all the coefficients only reflect the correlation, we take these as supportive evidence that foreign parent firms' patents are actually directly used in their affiliates' production. Thus, in the model, we will take into account that technologies introduced directly into China are utilized in the production of multinational affiliates,[8] in addition to affiliates' own innovation.

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, 7.56% of patents applied by multinational affiliates between 2000 and 2015 were sold to domestic firms, and 2.36% of patents applied

[8] This model setting is consistent with the broad multinational literature (e.g., Ramondo and Rodríguez-Clare, 2013; Tintelnot, 2017; Arkolakis et al., 2018), which typically assumes that multinational affiliates' production technology comes from their headquarters.

Table 2: Association between Firm Sales and Patents

Dependent Variable	$\log(sales_{i,t})$			
	All Firms	Multinational	Multinational	Multinational
$\log(1 + cumul\_patent_{i,t})$	0.140***	0.110***	0.106***	0.030
	(0.008)	(0.024)	(0.024)	(0.019)
$\log(1 + cumul\_patent\_par_{i,t})$			0.143***	0.091***
			(0.025)	(0.019)
Firm-level Controls	No	No	No	Yes
Industry-Year Fixed Effects	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes
Obs	1,519,236	123,522	123,522	122,836
R-squared	0.891	0.892	0.892	0.913

Notes: In this table, we present the results from regression (1). Firm-level controls include capital stock, employment, and dummies of firms' ownership structure (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% ***.

by their foreign parent firms between 2000 and 2015 were sold to domestic firms. Licensing occurs much less frequently: only 0.37% of patents applied by multinational affiliates between 2000 and 2015 were licensed to domestic firms, and the percentage drops to 0.09% for their foreign parent firms' patents. 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. Recent evidence (e.g., HMP, Bai et al., 2020) suggests that technology transfers usually occur through joint ventures (JVs). As shown in Table 1, joint ventures accounted for 54% of all multinational affiliates' patent applications, which suggests that joint ventures potentially play a big role in transitioning multinationals' innovation into China's domestic firms. Using our data on manufacturing firms, we find that for Chinese firms, becoming an owner of a joint venture was associated with higher sales and patent applications per year, as shown by Appendix Table A.4. This suggestive evidence is consistent with the finding in Bai et al. (2020) showing that in the Chinese automobile industry, affiliated domestic automakers tend to adopt the quality strengths of their joint venture partners. Given the importance of joint ventures in transferring technologies, in the baseline calibration of the quantitative model, we will consider all patents held by joint ventures as also being transferred to China and reflecting Quid Pro Quo policy.

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:	7,052	7.56%	1,249	1.34%	844	0.90%
Joint Ventures	3,684	7.28%	363	0.72%	267	0.53%
Foreign Parent Firm	9,061	2.36%	583	0.15%	447	0.12%
Panel B: Patent Licensing	Licensed to Domestic Firm		Licensed to Multinational Affiliate			
	Count	Fraction	Count	Fraction	Only JVs	Fraction (JVs)
Multinational Affiliate:	343	0.37%	73	0.08%	43	0.05%
Joint Ventures	244	0.48%	44	0.09%	34	0.07%
Foreign Parent Firm	341	0.09%	301	0.08%	147	0.04%

Panel C: Citations per Patent		Cited by Multinational Affiliates' Patents	
	Cited by Domestic Patents	All Multinational Affiliates'	Only JVs'
Multinational Affiliate:	0.73	0.31	0.18
Joint Ventures	0.74	0.31	0.29
Foreign Parent Firm	0.31	0.06	0.04

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.

Technology Spillovers. We now explore indirect technology spillovers from multinational affiliates (and their foreign parent firms) to domestic firms. We first look at citations, which are commonly used in the literature to measure the strength of knowledge spillovers. As shown by Table 3, we find that each multinational affiliate's patent applied between 2000–2015 on average received 0.73 citations from patents by domestic firms (in comparison, the average patent between 2000–2015 received 0.69 citations from patents by domestic firms). In contrast, their foreign parent firms' patents were cited less frequently, each on average receiving 0.31 citations from patents by domestic firms.

Citations may imperfectly capture all the knowledge spillovers, as firms do not necessarily cite all the patents that contribute to their innovations. As an additional analysis, we also explore the spillover measure proposed by Bloom, Schankerman and Van Reenen (2013). 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 $T_{i,\tau}$ is the share of firm i's patents in technology class τ. We consider 132 3-digit IPC categories as technology classes. For firm i and firm j, we construct the similarity between two firms' technology bundles according to Jaffe (1986):

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

Thus, the index $\rho_{i,j}$ 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 $\rho_{i,j}$ between each local firm and 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:

$$fdi\_spillover_{i,t} = \sum_{j \in \mathbb{M}} \rho_{i,j} \times patent_{j,t}, \tag{3}$$

$$par\_spillover_{i,t} = \sum_{j \in \mathbb{I}} \rho_{i,j} \times patent_{j,t}, \tag{4}$$

where $\mathbb{M}$ and $\mathbb{I}$ denote the set of multinational affiliates and their foreign parent firms, respectively. $patent_{j,t}$ is the amount of patent applications for firm j in year t.[9]

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

$$y_{i,t} = \beta_1 \log(1 + fdi\_spillover_{i,t}) + \beta_2 \log(1 + par\_spillover_{i,t}) + \alpha \mathbf{X}_{i,t} + \mu_i + \gamma_{s(i),t} + \epsilon_{i,t} \tag{5}$$

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

Table 4 presents the regression results. We use the logarithm of one plus the number of patent applications as the dependent variable in Columns (1)–(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

[9] 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 $patent_{j,t}$.

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

Dependent Variable	$\log(1+patent_{i,t})$				Innovation Status ($patent_{i,t}$>0)			
	OLS (1)	OLS (2)	2SLS (3)	2SLS (4)	OLS (5)	OLS (6)	2SLS (7)	2SLS (8)
$\log(1+fdi\_spillover_{i,t})$	0.027***	0.027***	0.035**	0.025	0.021***	0.021***	0.050***	-0.049
	(0.002)	(0.002)	(0.017)	(0.051)	(0.002)	(0.002)	(0.012)	(0.031)
$\log(1+par\_spillover_{i,t})$	0.058***	0.057***	0.227***	0.393***	0.056***	0.056***	0.095***	0.436***
	(0.004)	(0.004)	(0.057)	(0.119)	(0.004)	(0.004)	(0.036)	(0.091)
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	1,416,145	1,396,006	1,396,006	1,396,006	1,416,145	1,396,006	1,396,006	1,396,006
R-squared	0.015	0.015	0.000	0.013	0.012	0.013	0.000	0.001
Instrument			ind shift	WTO			ind shift	WTO
First-stage F			1354.01	220.61			1354.01	220.61

Notes: In this table, we present the results from regression (5). Firm-level controls include capital stock, employment, and dummies of firms' ownership structure (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 10 for details). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are clustered at the firm level in case that there may be autocorrelation of errors. Significance levels: 10% *, 5% **, and 1% ***.

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 Bartik-type instrument:

$$iv\_fdi\_spillover^1_{i,t} = \sum_s \left(\sum_{j \in \mathbb{M}_s} \rho_{i,j} \times patent_{j,2000} \right) \frac{fdi\_firmnum_{s,t}}{fdi\_firmnum_{s,2000}}. \tag{6}$$

Here, we first compute the firm's spillovers from multinational affiliates in each 4-digit industry s in 2000, $\sum_{j \in \mathbb{M}_s} \rho_{i,j} \times patent_{j,2000}$. 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 (6) 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:

$$iv\_fdi\_spillover^2_{i,t} = \sum_s \left(\sum_{j \in \mathbb{M}_s} \rho_{i,j} \times patent_{j,2000} \right) \times encourage_s \times post\_WTO_t, \qquad (7)$$

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).[10]

In Columns (3)–(4), we perform the IV regressions by separately applying the instruments constructed in equations (6) and (7) (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

[10] 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:

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

where we weight the firm-level exposure to other industries' characteristics by technology similarity to be consistent with equation (7). In the regressions, we allow for time-variant coefficients on x_i.

TFP) and their 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),[11] in Appendix Table A.6,[12] 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 the magnitude of this channel.

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 TFP 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 quantify the impact of multinational activities on China's domestic innovation, we build upon the framework of HMP by introducing two key modifications to their model based on our empirical evidence. Firstly, given that a share of multinationals' innovation takes place in China, we permit multinationals to accumulate technology specific to the host country's market. This aligns with the reality that multinationals can generate new knowledge and technologies that cater to the local market (Bilir and Morales, 2020). Secondly, since multinational firms produce positive spillover impacts on domestic firms' innovation, we integrate knowledge spillovers into the production function of new technology. This allows us to cap-

[11]We do not use Poisson regressions as suggested by Silva and Tenreyro (2006) because our independent variables (spillovers from multinational affiliates or their foreign parent firms) also contain zero values.

[12]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.

ture the extent to which knowledge accumulated by one firm can spill over and benefit other firms in the same country. Our model is designed to be parsimonious, while still capturing the key features of the relationship between multinationals and domestic innovation.

The world has many countries. Following HMP, we utilize an aggregate production function that combines production across firms originating from a given country. Our model embeds aggregate technologies in a multicountry general equilibrium framework that features two types of firms: multinationals with non-transferred technology capital and appropriators with transferred technology capital. To index countries, we use i or j: a subscript index refers to the country where production (innovation) occurs, while a superscript index denotes the origin country of multinational firms.

3.1 Multinational Problem

We consider that all multinational firms produce a homogeneous good, which can be used for consumption and investments. Consider the aggregate output of the multinational firm originating from country i and producing in host country j:

$$Y^i_{j,t} = A^i_{j,t} \left(q^i_{j,t} M^i_{j,t}\right)^{\phi} \left[\left(K^i_{j,t}\right)^{\alpha} \left(L^i_{j,t}\right)^{1-\alpha}\right]^{1-\phi}, \tag{8}$$

where $A^i_{j,t}$ captures the productivity level. For overseas production of multinational firms ($j \neq i$), $A^i_{j,t}$ also captures the degree of openness as well as barriers to applying the technologies from country i to country j (Ramondo and Rodríguez-Clare, 2013). $0 < \phi < 1$ captures the importance of technology capital in production relative to non-technology capital and labor, and $0 < \alpha < 1$ captures the importance of non-technology capital in production.

The production uses technology capital, $M^i_{j,t} = M^{i,o}_{j,t} + M^{i,h}_{j,t}$, which contains knowledge brought from the origin country, $M^{i,o}_{j,t}$, and the technology capital invested in host country j, $M^{i,h}_{j,t}$, with the intensity of using technology capital denoted as $q^i_{j,t} \in [0, 1]$. The stock of technology capital created by origin country i can be used nonrivalrously across all host countries (in our Chinese data, it mainly reflects patents held by foreign parent firms). But we still index it with subscript j for headquarters' technology capital available in host country j to capture that host countries may be engaged in Quid Pro Quo policies, which mean that multinational firms need to transfer technology for market access. For abroad production of multinational firms, the production also uses technology capital invested by the multinational firm in host country j, $M_{j,t}^{i,h}$, which can be thought of as market-specific investments and can only be used in host country j (in our Chinese data, it mainly reflects patents directly held by multinational affiliates registered in China, as most of their innovation is done within China). The difference in geographical applicability between parents' and affiliates' innovation is consistent with recent findings by Bilir and Morales (2020) who 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. The production also uses non-technology capital $K_{j,t}^i$ and labor $L_{j,t}^i$.

Given the production function $Y_{j,t}^i$, we can characterize the problem for multinationals originating from country i as:

$$\begin{aligned}
\max_{\{L_{j,t}^i, I_{j,t}^i, L_{j,t}^{i,e}, L_{i,t}^e, q_{j,t}^i\}} \sum_t p_t & \left[\sum_j \left(Y_{j,t}^i - W_{j,t} L_{j,t}^i - I_{j,t}^i - W_{j,t} L_{j,t}^{i,e} \right) - W_{i,t} L_{i,t}^e \right] \\
\text{s.t. } K_{j,t+1}^i &= (1-\delta_K) K_{j,t}^i + I_{j,t}^i \;\forall\, j \\
M_{j,t+1}^{i,o} &= (1-\delta_M)\left(1 - h_{j,t}(q_{j,t}^i)\right) M_{j,t}^{i,o} + \phi_{i,t}(L_{i,t}^e; \widetilde{M}_t) \\
M_{j,t+1}^{i,h} &= (1-\delta_M)\left(1 - h_{j,t}(q_{j,t}^i)\right) M_{j,t}^{i,h} + \phi_{j,t}^i(L_{j,t}^{i,e}; \widetilde{M}_t).
\end{aligned} \tag{9}$$

In the first line, p_t is the Arrow-Debreu price. $W_{j,t}$ denotes wage per unit of labor in host country j. $I_{j,t}^i$ is the amount of non-technology capital investments in host country j. $L_{j,t}^{i,t}$ and $L_{i,t}^e$ are the amount of R&D workers hired in host country j and headquarter country i, respectively. The second line captures the law of motion for non-technology capital.

The third line of equation (9) refers to the law of motion for technology capital from headquarter country i. We assume that the function $h_{j,t}(q_{j,t}^i)$ is weakly increasing in the intensity choice $q_{j,t}^i$ and weakly convex, capturing the Quid Pro Quo policy—the more technology capital brought in from overseas, the greater the required transfer. If multinational firms produce in their origin country, there is no Quid Pro Quo policy, $h_{i,t}(q_{i,t}^i) = 0$, and $q_{i,t}^i = 1$. We consider that innovation requires hiring workers. The increment in technology capital originating from country i depends on the amount of R&D workers hired in the headquarters, $L_{i,t}^e$, and the current state of technology capital across the globe as summarized by vector $\mathbf{M}_t$.

We parameterize $\phi_{i,t}(L^e_{i,t};\mathbf{M}_t)$ as:

$$\phi_{i,t}(L^e_{i,t};\mathbf{M}_t) = A^e_{i,t}(M^i_{i,t})^{-\gamma}\left(\sum_{j'}\tau^{j'}_{i,t}q^{j'}_{i,t}M^{j'}_{i,t}\right)(L^e_{i,t})^{\psi}. \tag{10}$$

$A^e_{i,t}$ denotes the efficiency of producing new technology in country i. The spillover effects on domestic technology sum up the spillover effects of technology capital brought from each country to country i, $\tau^{j'}_{i,t}q^{j'}_{i,t}M^{j'}_{i,t}$, where $\tau^{j'}_{i,t}$ captures that there can be barriers to accessing the technologies from country j', due to reasons such as endowments, development levels, or geographic distance (e.g., Acemoglu and Zilibotti, 2001; Comin and Hobijn, 2010; Buera and Oberfield, 2020). We normalize the barriers to accessing domestic technology levels to 1, $\tau^i_{i,t} = 1$. We follow Atkeson and Burstein (2019) to model $(M^i_{i,t})^{-\gamma}$, which captures that there may be diminishing returns to existing technology stock in the production of new technology capital. In the case of $\gamma = 0$ (constant returns to scale), new technology capital depends proportionally on current knowledge stock, which leads to a positive growth rate in the steady state as assumed in the classical endogenous growth literature (Romer, 1990; Grossman and Helpman, 1991). However, the recent literature finds that the productivity of creating new technology tends to decline with knowledge stock (Bloom et al., 2020), indicating $\gamma > 0$ which will be our setting in the quantitative analysis. Finally, as the literature typically finds diminishing returns of innovation efforts (see Acemoglu et al. (2018) for a review), we assume $\psi \in (0, 1)$ for the convexity of innovation returns.

Finally, the last line of equation (9) governs the evolution for market-specific technology capital in host country j. We assume that for multinational firms originating from country i, the increment in market-specific technology capital in host country j follows the same production function except for different levels of efficiency: $\phi^i_{j,t}(L^{i,e}_{j,t};\mathbf{M}_t) = A^{i,e}_{j,t}\phi_{i,t}(L^{i,e}_{j,t};\mathbf{M}_t)/A^e_{i,t}$, where $L^{i,e}_{j,t}$ is the amount of R&D workers hired in host country j, and $A^{i,e}_{j,t}$ denotes the efficiency of producing new technology capital in host country j.

3.2 Appropriator's Problem

We assume that in each country i, there is an appropriator. We make this assumption for the sake of convenience, as we need to model agents that receive transferred capital. The appropriator receives the technology capital transferred from multinational firms and maximizes the present value of profits. We use the tildes to distinguish the choices of appropriators in country i from those of multinational firms. The production technology is:

$$\widetilde{Y}_{i,t} = A^i_{i,t}\left(\widetilde{M}_{i,t}\right)^{\phi}\left[\left(\widetilde{K}_{i,t}\right)^{\alpha}\left(\widetilde{L}_{i,t}\right)^{1-\alpha}\right]^{1-\phi}. \tag{11}$$

The appropriator's problem can be written as:

$$\begin{aligned} &\max_{\{\widetilde{L}_{i,t},\widetilde{I}_{i,t}\}} \sum_t p_t\left(\widetilde{Y}_{i,t} - W_{i,t}\widetilde{L}_{i,t} - \widetilde{I}_{i,t}\right) \\ &\qquad \text{s.t. } \widetilde{K}_{i,t+1} = (1-\delta_K)\widetilde{K}_{i,t} + \widetilde{I}_{i,t} \\ &\qquad\quad \widetilde{M}_{i,t+1} = (1-\delta_M)\widetilde{M}_{i,t} + (1-\delta_M)\sum_j h_{i,t}(q^j_{i,t})M^j_{i,t}, \end{aligned} \tag{12}$$

where the appropriator chooses new investments in non-technology capital, $\widetilde{I}_{i,t}$, and the amount of labor to hire, $\widetilde{L}_{i,t}$, to maximize the present value of profits.

3.3 Households

Households choose sequences of consumption $C_{i,t}$ and labor supply $L_{i,t}$ to maximize the lifetime utility:

$$\begin{aligned} &\max_{\{C_{i,t},L_{i,t}\}} \sum_{t=0} \beta^t\left[\log(C_{i,t}/N_{i,t}) + \psi\log(1 - L_{i,t}/N_{i,t})\right]N_{i,t} \\ &\sum_{t=0} p_t C_{i,t} \leqslant \sum_{t=0} p_t\left(W_{i,t}L_{i,t} + D_{i,t}\right) + B_{i,0} \end{aligned} \tag{13}$$

$N_{i,t}$ is the amount of population in country i. We consider that multinationals from origin country i are owned by households in country i. Thus, the dividend $D_{i,t}$ includes the profits of appropriators in country i and the profits of multinationals that originate from country i. $B_{i,0}$ is the initial asset holding for households in country i.

3.4 Equilibrium

We now define a sequential equilibrium of the model economy. For each period t, the goods market, the asset market, and the labor market shall all be clear. We consider that the homogeneous good can be freely traded across countries. Thus, the goods market clearing in period t requires:

$$\sum_i \left[\widetilde{Y}_{i,t} + \sum_j Y_{i,t}^j \right] = \sum_i \left[C_{i,t} + \widetilde{I}_{i,t} + \sum_j I_{i,t}^j \right], \tag{14}$$

where the total output equals the total consumption and investments. In the equilibrium, the borrowing of assets shall be equal to the lending of assets, implying $\sum_i B_{i,t} = 0$. The labor market is clear for every country, implying that:

$$L_{i,t} = \sum_j L_{i,t}^j + \widetilde{L}_{i,t} + L_{i,t}^e + \sum_j L_{i,t}^{j,e}, \tag{15}$$

where the labor supply equals the labor demand in both production and innovation.

3.5 Main Mechanisms

To analytically understand the main mechanisms, we make several simplifying assumptions. We consider only two periods, $t = 0, 1$, and focus on a country i without production in other countries $A_{j,t}^i = 0 \ \forall \ j \neq i$. We also abstract from non-technology capital, $\alpha = 0$, and assume the diminishing returns of new technology to existing technology to be zero, $\gamma = 0$. If the firm in country i has positive investments in technology capital in the initial period, then the first-order condition of equation (9) with regard to R&D personnel $L_{i,0}^e$ implies:

$$\underbrace{p_1 A_{i,1}^i \phi (M_{i,1}^i)^{\phi-1} (L_{i,1}^i)^{1-\phi}}_{\text{marginal revenues of one unit of technology}} = \underbrace{\frac{p_0 W_{i,0}}{A_{i,0}^e \psi (L_{i,0}^e)^{\psi-1} \sum_{j'} \tau_{i,0}^{j'} q_{i,0}^{j'} M_{i,0}^{j'}}}_{\text{marginal costs of one unit of technology}}. \tag{16}$$

Figure 3 displays the relationship between the level of technology capital in $t = 1$ and the corresponding marginal revenues and marginal costs of innovation. Due to the diminishing returns of technology capital in production as $\phi < 1$, the marginal revenues exhibit a negative relationship with the level of technology capital in $t = 1$, whereas the marginal costs remain constant and are represented by a horizontal line regardless of the amount of technology capital in $t = 1$. The point where the marginal revenue and marginal cost curves intersect determines the optimal level of technology capital in $t = 1$, which subsequently determines the amount of investment in technology capital in $t = 0$, given initial technology capital $M_{i,0}^i$.

We now proceed to study how multinational entry affects domestic firms' innovation. Given equation (16), we can derive the following proposition.

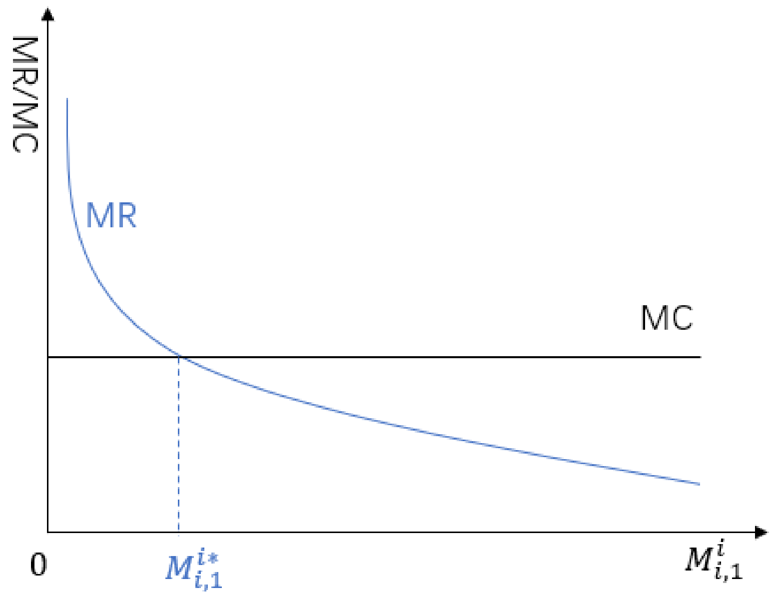


Figure 3: Marginal Revenues and Marginal Costs of Investing in Technology Capital

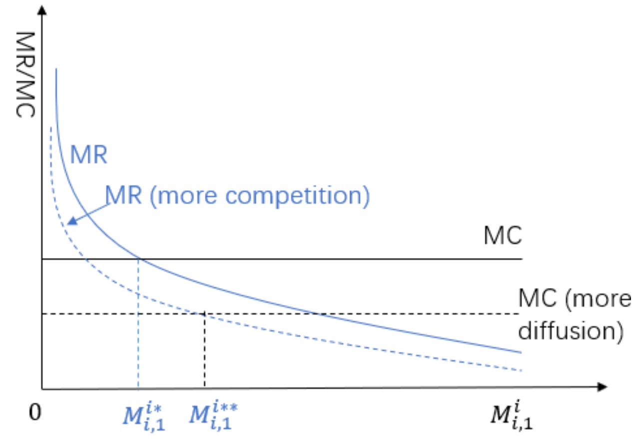
Proposition 1 (Effect of Multinationals in Two-period Model) *In the two-period model, all else being equal, we have:*
(1) Higher knowledge spillovers from multinationals increase domestic firms' technology investments, leading to higher domestic firms' technology stock $M_{i,1}^{i}$*; and*
(2) Given knowledge spillovers, more multinationals' production activities reduce domestic firms' employment $L_{i,1}^{i}$ *and technology investments, leading to lower domestic firms' technology stock* $M_{i,1}^{i}$.

Proof: See Appendix B.1.

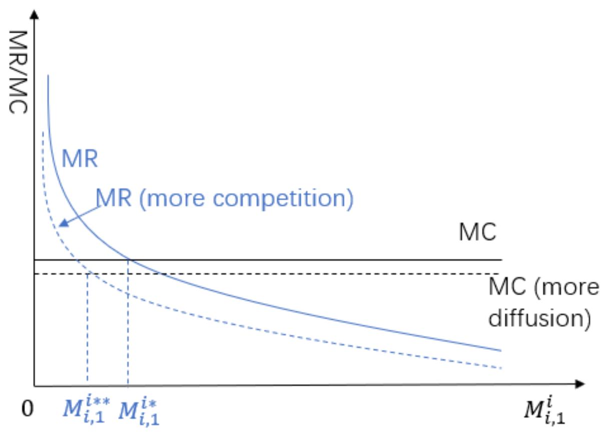
Proposition 1 shows that multinational entry can have both positive and negative effects on domestic firms' innovation activities. On the one hand, multinational firms bring new knowledge and technologies to the domestic market, which can reduce the marginal costs of innovation via spillover effects and lead to increased innovation activities. On the other hand, multinational entry can also lead to intensified competition and lower employment by domestic firms, which can reduce the marginal benefits for domestic firms to engage in innovation activities, reflecting the Schumpeterian effect which suggests that larger profits incentivize innovation (Schumpeter, 1942).[13]

Overall, the net effect of multinational entry on domestic innovation will depend on the balance between these two opposing forces. If the positive effects of knowledge spillovers outweigh the negative effects of increased competition as shown in Figure 4a, multinational

[13]These two opposite effects are also present in Bloom, Schankerman and Van Reenen (2013) who study the impact of firms on each other's innovation activities in the domestic setting.



(a) Scenario 1



(b) Scenario 2

Figure 4: Effects of Multinationals on Domestic Technology Capital

entry then has a positive impact on domestic innovation. However, if the negative effects of competition dominate as shown in Figure 4b, the impact of multinational entry on domestic innovation is then negative. In the next section, we will calibrate the model and assess the relative strengths of these two forces in the context of China.

4 Calibration

We now proceed to parameterize the model. We calibrate our model to the data in 2000–2015, consistent with the period examined in our empirical analysis. Our quantitative analysis focuses on two countries, namely China ($i = \mathcal{C}$) and the Rest of the World ($i = \mathcal{R}$). We focus on the steady state of the model. Thus, productivity levels $\{A^j_{i,t}, A^e_{i,t}, A^{j,e}_{i,t}\}$ and spillover effects $\tau^j_{i,t}$ remain time-invariant and are chosen to target the data moments averaged between 2000–2015. For ease of description, we drop the time subscript hereafter.

In what follows, we describe the calibration procedure and also discuss the model fit to the data moments.

4.1 Parameters Set without Solving the Model

Table 5 lists the parameters set without solving the model. We directly choose several parameters following HMP such that our calibration is closely comparable to theirs. We choose the discount rate as $\beta = 0.98$. We set the shares of technology capital, non-technology capital, and labor in production to be $\phi = 0.07$, $\alpha(1 - \phi) = 0.28$, and $(1 - \alpha)(1 - \phi) = 0.65$,

Table 5: Parameter Values

Parameter	**Notation**	**Value**	**Source**
Panel A: Parameters Set without Solving the Model			
Discount rate	β	0.98	HMP
Share of technology capital in production	ϕ	0.07	HMP
Share of non-technology capital in production	$\alpha(1-\phi)$	0.28	HMP
Share of labor in production	$(1-\alpha)(1-\phi)$	0.65	HMP
Depreciation rate of technology capital	δ_M	0.08	HMP
Depreciation rate of non-technology capital	δ_K	0.05	HMP
Elasticity of innovation returns to efforts	ψ	0.5	Acemoglu et al. (2018)
Diminishing returns to existing technology	γ	1.04	Atkeson and Burstein (2019)
ROW's population relative to China	$N_{\mathcal{R}}$	3.93	Penn World Table
Panel B: Parameters Set by Solving the Model			
Inno efficiency of firms from China and producing in China	$A_{\mathcal{C}}^{\mathcal{C},e}$	0.15	
Productivity of firms from ROW and producing in ROW	$A_{\mathcal{R}}^{\mathcal{R}}$	1.52	
Inno efficiency of firms from ROW and producing in ROW	$A_{\mathcal{R}}^{\mathcal{R},e}$	0.42	
Productivity of firms from ROW and producing in China	$A_{\mathcal{C}}^{\mathcal{R}}$	0.78	
Inno efficiency of firms from ROW and producing in China	$A_{\mathcal{C}}^{\mathcal{R},e}$	0.29	
Strength of knowledge spillovers from ROW to China	$\tau_{\mathcal{C}}^{\mathcal{R}}$	0.05	
Disutility of labor supply	ψ	0.63	
The degree of the Quid Pro Quo policy in China	$\delta_{\mathcal{C}}$	0.08	

respectively. The depreciation rates of technology capital and non-technology capital are respectively $\delta_M = 0.08$ and $\delta_K = 0.05$.[14]

Compared with HMP's framework, our main modification is the production function of new knowledge. The innovation literature already has many discussions on the convexity of the knowledge production function. For the elasticity of innovation returns to innovation efforts ψ, we set $\psi = 0.5$ according to the typical value used in the literature as reviewed by Acemoglu et al. (2018). For the degree of diminishing returns to existing technology stock γ, we set $\gamma = 1.04$ following Atkeson and Burstein (2019). In the robustness check, we also consider $\gamma = 1.32$ which allows our model to fit the historical evidence on diminishing returns to finding new ideas, as shown by Fernald and Jones (2014).

Finally, we normalize China's population to 1 and set the ROW's population to 3.93, which is the average relative population between the two countries in the 2000–2015 period, according to the Penn World Table (Feenstra, Inklaar and Timmer, 2015).

[14]HMP divide the non-technology capital into tangible capital and intangible capital, whereas we pool these two types of capital together.

4.2 Parameters Set by Solving the Model

Due to the lack of data[15] and our focus mainly on multinationals' operation in China, we abstract from China-originated firms' production and innovation in ROW. Firms that originate from ROW and produce in China are subject to the Quid Pro Quo policy. Following HMP, we use the functional form $h_{\mathcal{C}}(q) = \min\{\delta_{\mathcal{C}} q \exp(-10(1-q)), 1\}$,[16] where $\delta_{\mathcal{C}} > 0$ governs the degree of the Quid Pro Quo policy in China. We assume no Quid Pro Quo policy in ROW, $h_{\mathcal{R}}(q) = 0$. Finally, as only relative productivity levels are relevant for the model's outcomes, we normalize China's domestic productivity to unity, which means that $A_{\mathcal{C}}^{\mathcal{C}} = 1$.

We are thus left with a set $\mathcal{I}$ of 8 parameters to calibrate internally: innovation efficiency of firms originating from China and producing in China, $A_{\mathcal{C}}^{\mathcal{C},e}$; productivity and innovation efficiency of firms originating from ROW and producing in ROW, $\{A_{\mathcal{R}}^{\mathcal{R}}, A_{\mathcal{R}}^{\mathcal{R},e}\}$; productivity and innovation efficiency of firms originating from ROW and producing in China, $\{A_{\mathcal{C}}^{\mathcal{R}}, A_{\mathcal{C}}^{\mathcal{R},e}\}$; the strength of knowledge spillovers from ROW's firms to China's firms, $\tau_{\mathcal{C}}^{\mathcal{R}}$; disutility of labor supply, ψ; and the degree of the Quid Pro Quo policy in China, $\delta_{\mathcal{C}}$.

We jointly calibrate these parameters using the simulated method of moments (SMM) by minimizing the sum of squared differences between the model moments and the data moments:

$$\min_{\mathcal{I}} \sum_{k=1}^{8} \left(\frac{\text{data\_moment}_k - \text{model\_moment}_k}{\text{data\_moment}_k} \right)^2 . \tag{17}$$

We use the number of patents as a proxy for technology capital levels, following the innovation literature.[17] Specifically, we target the following moments: (1) the share of multinational firms' value added in China relative to China's GDP; (2) the ratio of ROW's GDP to China's GDP; (3) the employment-to-population ratio in China; (4) the relative amount of technology capital stock between ROW and China, which is proxied by the number of ROW's patents relative to that of China's domestic patents; (5) the number of multinational firms' patents in-

[15]We do not have data on the production and innovation of firms originating from China and producing in ROW.

[16]HMP use the functional form $h_{\mathcal{C}}(q) = \min\{\delta_{\mathcal{C}} q \exp(-\eta(1-q)), 1\}$ and set $\eta = 10$ in their baseline calibration. Due to the differences in model settings, they generate a different level of multinationals' intensity of using technology capital in China from ours. Because the intensity of using technology capital is unobserved, it is difficult to validate the choice of η. As a robustness check, we have also experimented with calibrating η such that our model can generate the same multinationals' intensity of using technology capital as HMP, and the quantitative findings remain very similar in this setting compared with our baseline results.

[17]In Section 6.1, we perform a robustness check by adjusting the patent numbers by patent quality, recomputing the data moments, and then recalibrating the model. We show that the quantitative results in this alternative case are very similar to our baseline results.

vented in China relative to that of China's domestic patents, which is based on the evidence in Section 2.2; (6) the ratio of technology capital to GDP in China; (7) proportional change in domestic firms' patent numbers in the absence of knowledge spillovers; and (8) the annual share of multinationals' knowledge transferred to China. Appendix B.2 provides details on data sources and how we calculate the model moments.

It is worth mentioning that to compute the last two moments, we use empirical evidence from Section 2.3. First, we use the reduced-form coefficients of domestic firms' innovation on multinational affiliates' and their foreign parent firms' technology spillovers to calculate proportional changes in domestic firms' patent numbers in the absence of knowledge spillovers. As we lack data for foreign patents unregistered in China's patent offices, this moment provides a conservative assessment of the reliance of China's innovation on knowledge spillovers from multinationals. To compute a comparable model moment, we perform an experiment in the model by setting Chinese firms' knowledge spillovers from multinationals to zero, $\tau_{\mathcal{C}}^{\mathcal{R}} = 0$, and then compute the model-based reduction in technology capital due to knowledge spillovers from multinationals.[18]

Secondly, to compute the share of multinationals' knowledge transferred to China, we aggregate all patent transactions and licenses from multinationals to Chinese domestic firms, and we also conservatively consider all patents held by joint ventures to be transferred to China.[19,20] Our data suggests that the annual share of multinationals' technology transferred to China is $h_{\mathcal{C}}(q_{\mathcal{C}}^{\mathcal{R}}) = 0.013$. Notably, given the modest percentages of technology transfers in overall multinationals' patent applications documented in Section 2.3, our estimate of the annual share of multinationals' technology transferred to China is lower than the cor-

[18]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.

[19]As we lack data for foreign patents unregistered in China's patent offices but used in the production of multinational affiliates in China, this calculation is also based on all patents registered in China's patent offices. It is likely that the rate of patents transferred to China tends to be lower for patents unregistered in China's patent offices than for those registered in China's patent offices, as knowledge flows tend to be localized for knowledge brought into a country (Buera and Oberfield, 2020). In Section 6.2, we consider alternative ways of calibrating the magnitude of the Quid Pro Quo policy and show that our quantitative results are robust.

[20]In the calibration, we do not specifically target the share of multinationals' patents filed with China's patent office to discipline the intensity of using technology by multinationals in China, due to the potential issue of unregistered technologies from multinationals. Instead, we adopt the approach of HMP, assuming that multinationals choose the intensity of technology utilization in China based on a tradeoff between maximizing profits and increasing the likelihood of technology transfers. Additionally, we also experimented with that the model was directly calibrated to reflect that the amount of technology capital used by multinationals in China constitutes exactly 21% of the total technology capital in China, as shown in Section 2. In this scenario, shutting down multinational activities can still lead to an approximately 20% decline in China's technology capital.

Table 6: Moments in the Model and the Data

Moment	Data	Model
Share of multinational firms' value added in China relative to China's GDP	0.07	0.07
Ratio of ROW's GDP to China's GDP	6.73	6.73
Employment-to-population ratio in China	0.57	0.57
Relative technology capital stock between ROW and China	5.91	5.91
Multinationals' technology capital created in China rel. to China's domestic technology capital	0.05	0.05
Ratio of technology capital to GDP in China	0.50	0.50
Proportional change in China's non-transferred technology capital without knowledge spillovers	-0.21	-0.21
Annual share of multinationals' knowledge transferred to China	0.013	0.013

responding estimate used by HMP (0.026-0.045 in 2000–2015). As the estimate in HMP was calibrated to match trends of GDP and FDI flows without relying on any innovation data, our estimate based on patent data thus provides a more precise measure of the amount of technology transferred from multinationals to China.

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 ROW and producing in ROW, $\{A_{\mathcal{R}}^{\mathcal{R}}, A_{\mathcal{R}}^{\mathcal{R},e}\}$, directly influence ROW's GDP and the amount of technology capital in ROW relative to China. Similarly, we can infer the productivity and innovation efficiency of firms originating from ROW and producing in China, $\{A_{\mathcal{C}}^{\mathcal{R}}, A_{\mathcal{C}}^{\mathcal{R},e}\}$, based on multinational firms' value added and innovation in China. Labor supply disutility ψ can be informed by examining the employment-to-population ratio in China. The strength of knowledge spillovers from ROW's firms to China's firms, $\tau_{\mathcal{C}}^{\mathcal{R}}$, 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, $\delta_{\mathcal{C}}$, can be inferred by the share of multinationals' knowledge transferred to China.

4.3 Calibration Results

Panel B of Table 5 displays the internally calibrated parameter values, which are reasonable compared to the existing literature. Specifically, we find that firms originating from ROW experience reduced productivity and innovation efficiency when they move to China, consistent with the challenges that multinationals face when operating in a foreign economy as documented in the trade literature (e.g., Ramondo and Rodríguez-Clare, 2013; Arkolakis et al., 2018). In addition, we observe that the productivity and innovation efficiency of firms originating from ROW and producing in ROW exceed those of China's domestic firms, which aligns with the higher GDP and patent amount per capita in ROW relative to China. We estimate the strength of knowledge spillovers from ROW's firms to China's firms as $\tau_C^{\mathcal{R}} = 0.05$. Given that the number of ROW patents relative to that of China's domestic patents is 5.91 and that the intensity of using technology capital of multinationals in China is $q_C^{\mathcal{R}} = 0.84$,[21] $\tau_C^{\mathcal{R}} = 0.05$ indicates that roughly 20% of the knowledge used in China's domestic innovation originates from ROW's firms, which is consistent with evidence on domestic citation shares in China (Liu and Ma, 2023).[22] Overall, Table 6 confirms that our model closely matches all the targeted moments.

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 now quantify China's gains in production and technology capital from entry of multinational firms. Firstly, we simulate a counterfactual scenario without multinational effects, where we set $A_C^{\mathcal{R}} = \tau_C^{\mathcal{R}} = 0$, resulting in no production and knowledge spillovers from multinational firms in China. The simulation outcomes are presented in Table 7, alongside the results from the baseline model for ease of comparison. Our analysis reveals that China's GDP and wage rate would decrease by 6.4% and 4.8%, respectively, without the production and knowledge spillovers from multinationals.[23] This contribution of multinationals to China's growth is similar in magnitude to the effects of several other important policies in recent decades, such as trade liberalization (Tombe and Zhu, 2019), migration cost reductions (Tombe and Zhu, 2019; Hao et al., 2020), or college education expansion (Ma, 2023).

[21] In HMP, they find $q_C^{\mathcal{R}}$ to be around 0.4 in 2000–2015, but their calibration considers a relative ratio of technology capital stock between ROW and China to be 19 (compared to 5.91 in our model's baseline calibration). We discuss the implication of using their relative ratio in our calibration in Section 6.1.

[22] Liu and Ma (2023) use global patent citation data and highlight China's high reliance on knowledge flows from abroad.

[23] The difference in the responses between GDP and wage rates primarily reflects that lower wage rates discourage labor supply, thus reducing the total amount of labor in China.

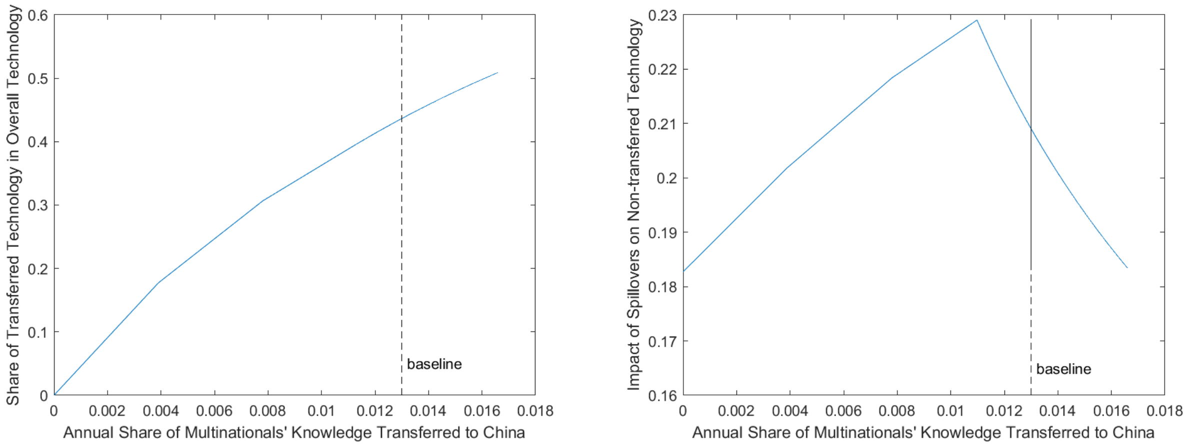
Table 7: China's Gains from Multinational Firms

	(1) Baseline	(2) No multinational production & spillovers ($A_C^{\mathcal{R}} = \tau_C^{\mathcal{R}} = 0$)	(3) No multinational spillovers ($\tau_C^{\mathcal{R}} = 0$)
China's GDP	0.942	0.882 (-6.4%)	0.933 (-1.0%)
China's wage rate	1.099	1.046 (-4.8%)	1.086 (-1.2%)
China's technology capital stock	0.472	0.301 (-36.2%)	0.416 (-11.9%)
non-transferred capital stock	0.266	0.301 (13.2%)	0.210 (-21.1%)
transferred capital stock	0.206	0 (-100%)	0.206 (0%)

If there were no multinational production and knowledge spillovers, China's total technology capital would drop by 36.2%, primarily due to the absence of knowledge transfers via the Quid Pro Quo policy. Interestingly, in this scenario, the technology capital generated by Chinese domestic firms ("non-transferred capital") would increase by 13.2%. As previously discussed in Section 3.5, multinationals influence Chinese firms' innovation through both knowledge spillovers (which reduce innovation costs) and intensified competition (which reduce innovation benefits). In our calibrated economy, the negative effects of heightened competition outweigh the positive effects of knowledge spillovers, resulting in the adverse net effects of multinationals on Chinese firms' technology capital stock.

In Column (3), we set $\tau_C^{\mathcal{R}} = 0$ to isolate the effects of knowledge spillovers from multinationals. Our analysis reveals that in this counterfactual scenario, the technology capital generated by Chinese domestic firms would decrease by 21.1% compared to the baseline model, reaffirming the positive effects of multinationals on China's technology via knowledge spillovers.[24] However, the proportional changes in GDP and wages in this scenario are considerably smaller than those in the scenario where both production and knowledge spillovers from multinationals are shut down. This is because multinationals can still produce output in China, even without knowledge spillovers.

[24]This outcome can be expected as the reduction in technology capital was one of our targeted moments in the calibration.



(a) Share of Transferred Capital

(b) Impact of Knowledge Spillovers

Notes: For each degree of Quid Pro Quo policy, we compute the impact of multinationals' knowledge spillovers on China's non-transferred technology based on comparing the proportional difference in China's non-transferred capital between the scenarios with and without multinational spillovers (similar to Columns 1 and 3 in Table 7).

Figure 5: Changes in Quid Pro Quo Policy

5.2 Quid Pro Quo Policy

5.2.1 Overall Impact of Quid Pro Quo Policy on Production and Technology

To assess the overall impact of the Quid Pro Quo policy on production and technology, we begin by simulating a scenario in which no Quid Pro Quo policy is in place. In this scenario, we set $\delta_C = 0$, causing multinational firms to always utilize all of their technology capital ($q = 1$) within China. Our findings reveal that, under these conditions, China's GDP would experience a decline of 2.9% compared to the baseline. Despite multinational firms increasing the intensity of technology usage in this scenario, the primary driver of China's GDP decline is the reduction in technology transfers. Consequently, the total technology capital in China would decrease by 27.3% in this hypothetical scenario.

5.2.2 Interaction between Quid Pro Quo Policy and Knowledge Spillovers

The Quid Pro Quo policy's technology transfers can influence the significance of knowledge spillovers in shaping Chinese firms' innovation activities. To examine this interaction, we vary parameter δ_C in Figure 5, which determines the Quid Pro Quo policy's degree, while keeping other parameters at their baseline values. We find that a higher degree of technology transfers from multinationals to China modifies the composition of China's technology capital stock, leading China to rely more on transferred technology capital rather than non-transferred technology capital generated by domestic firms, as illustrated in Figure 5a. In some sense, this change in composition could reflect Chinese firms' shift between technology adoption and innovation in response to changes in the economic policy environment, as highlighted in recent literature (König et al., 2022).

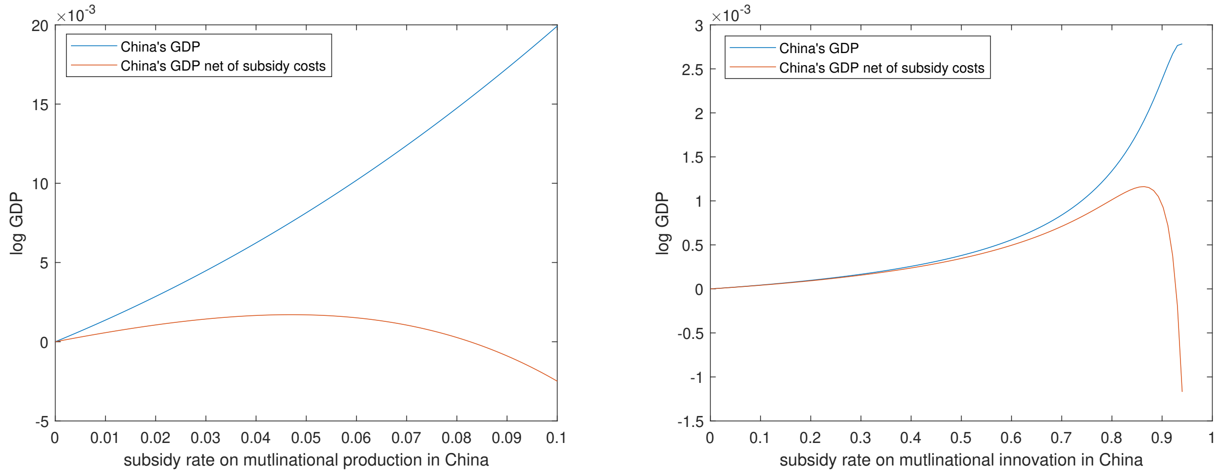
The Quid Pro Quo policy has two opposing effects on the strength of knowledge spillovers. On the one hand, with a higher degree of technology transfers, China becomes increasingly reliant on transferred technology capital. Consequently, China's non-transferred technology capital stock diminishes and becomes relatively smaller compared to multinationals' technology capital.[25] Thus, knowledge spillovers assume a greater role in influencing Chinese firms' innovative activities. On the other hand, faced with stronger technology transfers, foreign multinationals reduce their intensity of using technology capital in China, which in turn decreases the strength of knowledge spillovers in China. Due to the combined effects of these two forces, the Quid Pro Quo policy has a hump-shaped effect on the significance of knowledge spillovers in shaping Chinese firms' innovation, as shown by Figure 5b.

5.3 Subsidy on Multinationals

In developing countries, governments often allocate significant funds toward attracting foreign multinationals. One of the primary reasons behind this policy is to encourage technology spillovers to domestic firms (Amiti et al., 2023). Our model also identifies two externalities of multinationals' technology choices. Firstly, technology transfers from multinationals would increase China's technology capital. Secondly, knowledge spillovers would enhance the efficiency of China's domestic innovation. These externalities suggest that the amount of multinationals' technology capital may be suboptimal, and therefore, policies that incentivize the accumulation of technology capital by multinationals can be advantageous.

We will now examine a subsidy on multinationals' production in China. Specifically, the government will provide a subsidy, funded by lump-sum taxes, that amounts to a portion $x \geqslant 0$ of the output revenues produced by multinationals in China. We can consider x as an indicator of preferential tax treatment given to foreign multinationals over Chinese domestic

[25] Although multinationals' technology capital stock also contracts due to more technology transfers, this decline is less proportional than the decline in China's non-transferred technology capital. This is because multinationals' technology capital stock is much larger than China's technology capital stock, and thus a small change in technology transfers can significantly affect China's technology capital stock.



(a) Subsidy on Multinational Production

(b) Subsidy on Multinational Innovation

Figure 6: Subsidy on Multinationals in China

firms, which has been a longstanding practice in China (Chen et al., 2021).

In Figure 6a, we present the effects of varying subsidy rate x on China's log GDP under different subsidy rates, where we normalize China's log GDP in the baseline to zero for ease of comparison. Our findings indicate that higher subsidy rates for multinational production increase China's GDP, as they encourage multinational firms to hire more labor and accumulate more technology and non-technology capital, ultimately improving China's production capacity. However, higher subsidy rates also generate more financial costs for China, which can lead to over-investments (Romer, 2011). We observe that China's GDP net of subsidy costs follows a hump-shaped relationship with subsidy rates. At a tax rate of $x = 5\%$, we find the most significant increase (0.17%) in China's GDP net of subsidy costs, with China's overall GDP increasing by 0.76%.

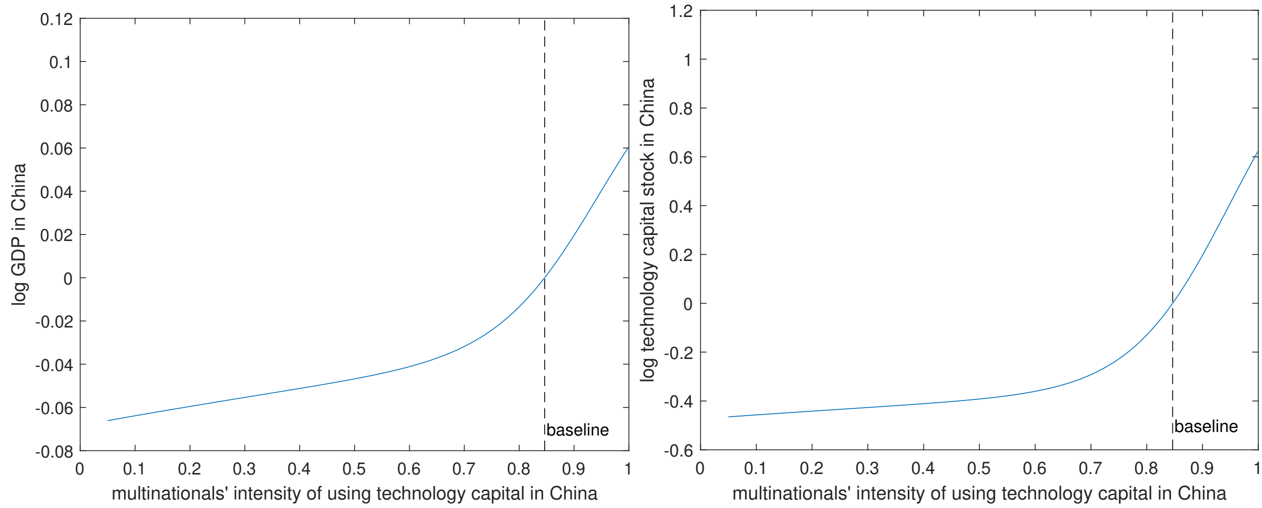
As mentioned earlier, our model's externalities are intertwined with the technology choices made by multinationals. Therefore, we examine a subsidy on multinationals' innovation in China as well. Specifically, we consider subsidizing a portion $x \geqslant 0$ of the innovation costs incurred by multinationals in China, which will also be funded by lump-sum taxes. In Figure 6b, we display the impact of subsidy rate x on innovation and plot the corresponding China's log GDP under different subsidy rates, where we normalize China's log GDP in the baseline to zero for comparison purposes. We have two key findings. First, compared to subsidizing multinationals' production, a subsidy solely on multinationals' innovation has a much smaller impact on China's GDP since subsidizing multinationals' production also directly affects their decisions on hiring workers and investing in non-technology capital.

Second, at tax rate $x = 86\%$, we find the largest increase (0.12%) in China's GDP net of subsidy costs, with China's overall GDP increasing by 0.19%. Here, to maximize the increase in China's GDP net of subsidy costs, the optimal tax rate $x = 86\%$ is much larger than the optimal tax rate $x = 5\%$ of subsidizing production. This is because subsidizing production would affect marginal returns to technology capital brought from headquarter countries and thus also change multinationals' innovation activities in their headquarter countries. As multinationals' innovation activities in China are much fewer than their innovation activities in headquarter countries, only subsidizing multinationals' innovation in China requires a much larger subsidy rate. Moreover, we find that at the optimal tax rates, the increase in China's GDP net of subsidy costs is similar between subsidizing multinationals' innovation and subsidizing multinationals' production, reassuring that the externalities of multinationals' technology choices are the major driver of the inefficiency of multinationals in the model.

5.4 Departure of Multinationals from China

China has long been recognized as the "world factory" and a significant export platform for foreign multinationals. However, while China's share of global manufacturing exports reached its peak in 2015, recent years have seen a gradual shift of (especially labor-intensive) manufacturing from China to other emerging nations with comparative advantages (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 technology capital for multinationals in China, $q_{\mathcal{C}}^{\mathcal{R}}$, which is based on the tradeoff between the current revenues (marginal benefits of raising $q_{\mathcal{C}}^{\mathcal{R}}$) and technology losses that affect future revenues (marginal costs of raising $q_{\mathcal{C}}^{\mathcal{R}}$). However, we did not take into account other drivers of multinational firms' decision to locate their production in China. To evaluate the quantitative effects of multinational firms' relocation from



(a) China's GDP (b) China's Technology Capital Stock

Figure 7: Multinationals' Relocation from China

China, we directly adjust multinationals' intensity of using technology capital in China.[26]

Figure 7a illustrates how China's GDP changes with varying multinational firms' intensity of using technology capital in China. As expected, a decrease in multinational firms' intensity leads to a decline in China's GDP. What is particularly noteworthy, however, is the amplification effect that occurs when multinational firms relocate from China. For instance, if multinationals' intensity of using technology capital in China is reduced by half from the baseline (0.84), China's GDP would decrease by 4.9%, with only 23% of this reduction attributable to the decrease in multinational firms' production in China. The significant amplification effects are mainly driven by the reduction in technology transfers resulting from the lower intensity of using technology capital for multinational firms, which reduces the technology capital stock available in China. Figure 7b demonstrates that if multinational firms' intensity of using technology capital in China is halved from the baseline (0.84), China's technology capital stock would decline by 33.4%.

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.

[26] This adjustment assumes that multinationals' intensity of using technology capital in China is exogenously determined and not based on the optimal choice of multinational firms. The goal of this exercise is to capture other influences that could alter multinational firms' willingness to locate their production in China.

6 Robustness

This section comprises a series of robustness checks for our quantitative findings. As our study focuses on technology capital, we will delve into the measurement of technology capital, examine various approaches to measuring the Quid Pro Quo policy, and investigate how different innovation function settings impact the outcomes.

We present a summary of the results in Table 9, 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 technology stock.

6.1 Measurement of Technology Capital Stock

Using Quality-adjusted Patent Numbers. The number of patents may not accurately depict the gap in technology capital stock between China and ROW, especially given the widespread concerns about the low quality of Chinese patents. To address this issue, we adjust the previously calculated patent numbers by 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). 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).[27] The first and second rows in Table 8 display the average patent quality for China and the ROW, respectively, and we also display the results for the US.[28] 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.

[27]Patent quality index 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. Patent quality index 6 includes the same components as index 4, along with the number of backward citations and the grant lag index.

[28]Appendix Figure A.2 illustrates the annual changes in PQI of patents from China, the US, and the ROW between 2000 and 2015.

Table 8: 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

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 use the quality difference between China's and the US's applications to EPO as a measure of the quality difference between China and the ROW. 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.

Table 8 imply that China's patent quality is 87% of the US level (averaged across two measures). Thus, we use this result to compute the quality-adjusted patent number of ROW relative to that of China, and this relative ratio is higher than the baseline data moment without dealing with patent quality. We then recalibrate all model parameters to match the revised targeted data moments.

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, China's technology capital relies more heavily on transferred capital due to the increased relative level of technology capital stock between ROW and China. Therefore, when multinational firms exit China, China's technology capital stock experiences a more significant decline. China's growing dependence on transferred technology capital also reduces the employment of firms using non-transferred technology capital, which intensifies competition effects and leads to a more significant negative impact of multinationals on Chinese firms' innovation activities.

Calibrating Relative Technology Capital Stock between China and ROW following HMP. HMP calibrated their model to conform with the overall trends of GDP and FDI flows, without utilizing any innovation data. They determined that, in equilibrium, China held approx-

Table 9: Impact of Multinationals on China: Robustness Checks

	GDP	Wage	Technology stock: All	Technology stock: Non-transferred	Technology stock: Transferred
Panel A: baseline model					
No multinational production & spillovers	-6.4%	-4.8%	-36.2%	13.2%	-100%
No multinational spillovers	-1.0%	-1.2%	-11.9%	-21.1%	0%
Panel B: quality-adjusted patents					
No multinational production & spillovers	-6.7%	-5.1%	-38.1%	17.0%	-100%
No multinational spillovers	-0.9%	-1.1%	-11.0%	-21.0%	0.1%
Panel C: calibrating relative technology capital stock between China and ROW following HMP					
No multinational production & spillovers	-9.8%	-7.7%	-53.9%	60.6%	-100%
No multinational spillovers	-0.4%	-0.6%	-6.0%	-20.9%	0%
Panel D: only considering patent transactions and licenses as technology transfers					
No multinational production & spillovers	-5.3%	-3.9%	-29.7%	0.6%	-100%
No multinational spillovers	-1.2%	-1.4%	-14.7%	-21.1%	0.2%
Panel E: calibrating magnitude of Quid Pro Quo policy following HMP					
No multinational production & spillovers	-8.0%	-6.1%	55.2%	33.0%	-100%
No multinational spillovers	-0.6%	-0.8%	-8.6%	-21.0%	0.1%
Panel F: diminishing returns to existing technology capital					
No multinational production & spillovers	-7.1%	-5.5%	-41.0%	4.8%	-100%
No multinational spillovers	-0.9%	-1.1%	-11.8%	-21.1%	0.2%
Panel G: alternative functional form of innovation function					
No multinational production & spillovers	-6.4%	-4.8%	-36.2%	13.2%	-100%
No multinational spillovers	-0.9%	-1.1%	-11.8%	-21.0%	0.2%

imately 5% of the world's technology capital in the 2000s. Rather than relying on patent numbers to compute the relative technology capital stock between ROW and China, we employ HMP's findings and aim to achieve a relative ratio of technology capital stock between ROW and China of 19 (compared to the baseline calibration of 5.91). All model parameters are then recalibrated to match the revised data moments.

As with the earlier scenario involving quality-adjusted patent numbers, multinationals exert a greater influence on China's GDP in the recalibrated model than in the baseline model. However, due to the more pronounced increase in the relative technology capital stock between the ROW and China in this case, compared to the previous scenario of quality-adjusted patent numbers, the impact of multinationals on China's production and technology capital becomes even more significant.

6.2 Quid Pro Quo Policy

Only Considering Patent Transactions and Licenses as Technology Transfers. In our calibration, to compute the share of multinationals' knowledge transferred to China, we considered all patents held by joint ventures to be transferred to China. As it is unclear whether the patents held by joint ventures are all transferred, we now only consider patent transactions and licenses as transfers. The resulting annual share of multinationals' technology transferred to China is much lower at $h_C(q_C^{\mathcal{R}}) = 0.003$ (0.013 in the baseline calibration). All model parameters are then recalibrated to meet the revised data moments.

Panel D of Table 9 indicates that multinationals have a lower 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 capital due 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.

Calibrating Magnitude of Quid Pro Quo Policy following HMP. According to HMP's estimates, the annual share of technology transferred by multinationals was between 0.026–0.045 during 2000–2015. To confirm the robustness of our findings, we adjust our calibration to target $h_C(q_C^{\mathcal{R}}) = 0.03$. Panel E of Table 9 illustrates that, in this scenario, multinationals have a more significant impact on China's GDP than in the baseline model. This is because China relies more on transferred capital, given the higher share of technology transferred by multinationals. This case is exactly the opposite of the scenario where technology transfers are considered only in terms of patent transactions and licenses.

6.3 Innovation Function

Diminishing Returns to Existing Technology Capital. To account for the degree of diminishing returns to existing technology stock, we initially set $\gamma = 1.04$ based on Atkeson and Burstein (2019). As a robustness check, we also consider the value $\gamma = 1.32$, allowing our model to fit the historical evidence on diminishing returns to finding new ideas (Fernald and Jones, 2014). We then recalibrate all the internally calibrated model parameters.

A higher value of γ implies that firms experience a more rapid increase in marginal costs of innovation with increasing technology capital, leading to a lower sensitivity of firms' innovative levels to changes in marginal benefits of innovation. This, in turn, results in smaller competition effects for firms using non-transferred technology and nearly unchanged effects of knowledge spillovers, which are targeted in our calibration. As a result, multinationals have a larger positive impact on China's GDP and technology capital, and their negative impact on China's innovative activities becomes smaller in magnitude.

Functional Form of Innovation Function. Our model assumes a linear relationship between innovation and knowledge spillovers: $\phi_{i,t}(L^e_{i,t}; \mathbf{M}_t) = A^e_{i,t}(M^i_{i,t})^{-\gamma} \left(\sum_{j'} \tau^{j'}_{i,t} q^{j'}_{i,t} M^{j'}_{i,t}\right) (L^e_{i,t})^{\psi}$. As a robustness check, we also consider a concave relationship between innovation and knowledge spillovers, expressed as $\phi_{i,t}(L^e_{i,t}; \mathbf{M}_t) = A^e_{i,t}(M^i_{i,t})^{-\gamma} \left(\sum_{j'} \tau^{j'}_{i,t} q^{j'}_{i,t} M^{j'}_{i,t}\right)^{\kappa} (L^e_{i,t})^{\psi}$, where $0 < \kappa < 1$. We follow HMP and set $\kappa = 0.05$. All internally calibrated model parameters are then recalibrated accordingly.[29]

Our analysis indicates that the recalibrated model generates results that are quantitatively comparable to those of the baseline model. This is because the modification made to the functional form of the innovation function solely pertains to knowledge spillovers. By targeting the impact of knowledge spillovers on innovation during calibration, the change in the functional form has a negligible effect on our quantitative findings.[30]

7 Conclusion

Multinational activities can 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

[29] Introducing $0 < \kappa < 1$ reduces the degree of diminishing returns to existing technology capital. To maintain the same degree of diminishing returns as in the baseline model, we adjust the value of parameter γ accordingly.

[30] However, due to the concavity of knowledge spillovers in the recalibrated model, we require a larger degree of knowledge spillovers from ROW to China ($\tau^{\mathcal{R}}_{\mathcal{C}}$) to maintain the same impact of knowledge spillovers on innovative activities as in the baseline model.

model suggests that without multinational production and knowledge spillovers, China's total technology capital would drop by 36%. The model also suggests that as a result of multinationals' technology transfers and spillovers, there are large amplification effects of multinational activities on China's GDP, and subsidizing multinational production or innovation 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 as well (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).

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

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

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.

Alviarez, Vanessa. 2019. "Multinational Production and Comparative Advantage." *Journal of International Economics*, 119.

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 Rodrıguez-Clare, and Stephen Yeaple. 2018. "Innovation and Production in the Global Economy." *American Economic Review*, 108(8): 2128–73.

Atkeson, Andrew, and Ariel Burstein. 2019. "Aggregate Implications of Innovation Policy." *Journal of Political Economy*, 127(6).

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/.*

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

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb. 2020. "Are Ideas Getting Harder to Find?" *American Economic Review*, 110(4).

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

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

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).

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

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.

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).

Choi, Jaedo, and Younghun Shim. 2023. "From Adoption to Innovation: State-Dependent Technology Policy in Developing Countries." *Working Paper*.

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.

Comin, Diego, and Bart Hobijn. 2010. "An Exploration of Technology Diffusion." *American Economic Review*, 100.

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.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review*, 105: 3150–82.

Fernald, John G., and Charles I. Jones. 2014. "The Future of US Economic Growth." *American Economic Review*, 104(5).

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

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

Grossman, Gene M., and Elhanan Helpman. 1991. "Quality Ladders in the Theory of Growth." *The Review of Economic Studies*, 58.

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

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.

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.

Hsieh, Chang-Tai, Peter J. Klenow, and Ishan Nath. 2023. "A Global View of Creative Destruction." *Journal of Political Economy Macroeconomics*, 1(2).

Hu, Albert Guangzhou, and Gary H. Jefferson. 2009. "A Great Wall of Patents: What is Behind China's Recent Patent Explosion?" *Journal of Development Economics*, 90.

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).

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).

Jia, Junxue, and Guangrong Ma. 2017. "Do R&D Tax Incentives work? Firm-level evidence from China?" *China Economic Review*, 46.

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

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

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).

Klette, Tor Jakob, and Samuel Kortum. 2004. "Innovating Firms and Aggregate Innovation." *Journal of Political Economy*, 112(5): 986–1018.

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).

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, 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.

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*.

Ramondo, Natalia, and Andrés Rodríguez-Clare. 2013. "Trade, Multinational Production, and the Gains from Openness." *Journal of Political Economy*, 121.

Romer, David. 2011. *Advanced Macroeconomics 4th Edition.* McGraw Hill.

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

Santacreu, Ana Maria. 2023. "Dynamic Gains from Trade Agreements with Intellectual Property Provisions." *Working Paper*.

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.

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).

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

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.

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

A Additional Tables and Figures

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

Regions	Number of Firms	Share
Taiwan	56,081	20.3%
Korea	35,149	12.7%
The United States	34,939	12.7%
Japan	33,423	12.1%
British Virgin Islands	14,136	5.1%
Singapore	13,154	4.8%
Macau	8,625	3.1%
Canada	7,575	2.7%
Australia	5,462	2.0%
Germany	4,897	1.8%
The United Kingdom	4,563	1.7%
Samoa	3,700	1.3%
Albania	3,080	1.1%
Malaysia	3,078	1.1%
France	2,911	1.1%
Italy	2,888	1.0%

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: Distribution of the Number of Patent Applications across Multinational Affiliates and their Foreign Parent Firms

	Obs	Mean	Median	1% Percentile	99% Percentile
Multinational Affiliates	276,104	0.34	0	0	4
Joint Ventures	100,186	0.51	0	0	7
Multinational Affiliates (>0)	7,780	12.00	2	1	167
Joint Ventures (>0)	4,205	12.03	2	1	161
Foreign Parent Firms	273,175	1.41	0	0	1
Foreign Parent Firms (>0)	2,959	129.92	4	1	2,566

Notes: The statistics are computed based on the firm-level total number of patent applications between 2000–2015.

Table A.3: Summary Statistics for ASM

	All Firms			Domestic Firms			Multinational Affiliates		
	Obs	Mean	Std	Obs	Mean	Std	Obs	Mean	Std
log(sales)	1,724,290	9.94	1.38	1,592,950	9.91	1.37	131,340	10.41	1.35
log(capital)	1,725,543	8.24	1.72	1,594,637	8.20	1.71	130,906	8.75	1.75
log(employment)	1,739,967	4.70	1.15	1,608,382	4.68	1.15	131,585	4.96	1.14
TFP (labor share=2/3)	1,289,194	2.78	1.11	1,190,713	2.77	1.11	98,481	2.87	1.06
TFP (HK2009)	1,282,703	6.00	1.68	1,184,500	5.98	1.69	98,203	6.26	1.60
log(1+cumul_patent)	1,749,167	0.02	0.17	1,617,233	0.02	0.16	131,934	0.02	0.19
log(1+cumul_patent_par)							131,934	0.10	0.68
log(1+fdi_spillover)				1,617,233	0.16	0.66			
log(1+par_spillover)				1,617,233	0.52	1.98			

Notes: The statistics are computed based on firm-year observations. Sales, capital, and employment are in terms of thousands of RMB. We consider two different measures for the labor share in the Cobb-Douglas function: (a) we set the labor share to be $\frac{2}{3}$ 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). In constructing the second measure, because there are extensive labor distortions in China, we follow Hsieh and Klenow (2009) to proxy China's industry-level labor share using the corresponding industry-level measure from the US, and we consider the elasticity of demand substitution between firms within an industry is 3. The measures regarding patents and spillovers are described in the main text in Section 2.

Table A.4: Suggestive Evidence on the Effect of Owning Joint Ventures

Dependent Variable	$\log(sales_{i,t})$		$\log(1+patent_{i,t})$	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
$\log(1+cumul\_patent_{i,t})$	0.141***	0.070***		
	(0.009)	(0.007)		
$own\_joint\_venture_{i,t}$	0.111***	0.060**	0.031***	0.029***
	(0.016)	(0.013)	(0.006)	(0.006)
Firm-level Controls	No	Yes	No	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	1,395,493	1,385,256	1,416,145	1,396,006
R-squared	0.890	0.907	0.586	0.587

Notes: In this table, we present suggestive evidence on the effect of forming joint ventures on domestic firms. The independent variable $own\_joint\_venture_{i,t}$ is a dummy variable that equals 1 if the Chinese domestic firm was an equity owner of at least one joint venture at year t. Firm-level controls include capital stock, employment, and dummies of firms' ownership structure (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% ***.

Table A.5: Association between Technology Spillovers and Domestic Firms' Technology

Dependent Variable	log($sales$)				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)
log(1+$fdi\_spillover$)	0.041***	0.019***	0.066***	0.052	-0.007	0.011*	0.036	-0.018	0.005	0.017*	0.054	-0.021
	(0.004)	(0.004)	(0.022)	(0.123)	(0.006)	(0.006)	(0.026)	(0.059)	(0.009)	(0.009)	(0.040)	(0.088)
log(1+$par\_spillover$)	0.269***	0.164***	0.141*	0.117	0.082***	0.154***	0.192**	0.267**	0.196***	0.230***	0.282**	0.387**
	(0.012)	(0.010)	(0.073)	(0.292)	(0.015)	(0.015)	(0.092)	(0.125)	(0.023)	(0.022)	(0.138)	(0.188)
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	1,395,493	1,385,256	1,385,256	1,385,256	994,888	994,869	994,869	994,869	989,897	989,878	989,878	989,878
R-squared	0.003	0.140	0.140	0.140	0.001	0.058	0.058	0.058	0.001	0.074	0.074	0.074
Instrument			ind	WTO			ind	WTO			ind	WTO
First-stage F			1356.70	105.89			1494.98	1913.95			1494.15	1914.26

Notes: In this table, we replicate the regressions in Columns (1)–(4) of Table 4 with different dependent variables. Firm-level controls include capital stock, employment, and dummies of firms' ownership structure (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, payroll, 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 $\frac{2}{3}$ 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). In constructing the second measure, because there are extensive labor distortions in China, we follow Hsieh and Klenow (2009) to proxy China's industry-level labor share using the corresponding industry-level measure from the US, and we consider the elasticity of demand substitution between firms within an industry is 3. Columns (3), (7), and (11) use the instrument constructed in equation (6) (we analogously construct the instrument for spillovers from foreign parent firms). Columns (4), (8), and (12) use the instrument constructed in equation (7) (we analogously construct the instrument for spillovers from foreign parent firms). 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.6: Impact of Technology Spillovers on Domestic Firms' Innovation

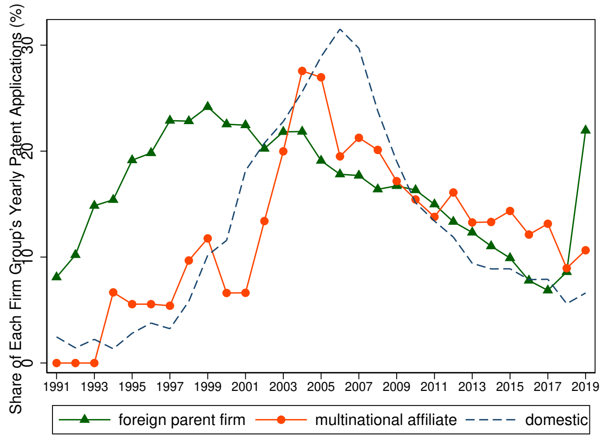
Dependent Variable	$patent_{i,t}$			
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
$spillover_{i,t}$	0.00017**	0.00017**	0.00017**	0.00021*
	(0.00008)	(0.00008)	(0.00009)	(0.00012)
Firm-level Controls	No	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
Obs	1,416,145	1,396,006	1,396,006	1,396,006
R-squared	0.003	0.003	0.003	0.003
Instrument			ind shift	WTO
First-stage F			1621.08	801.42

Notes: In this table, we present the results from regression (5). The independent variable is constructed as $spillover_{i,t} = fdi\_spillover_{i,t} + par\_spillover_{i,t}$, 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 capital stock, employment, and dummies of firms' ownership structure (e.g., private or state-owned firms). We report first-stage Kleibergen-Paap F-statistic on the excluded instrument. Standard errors are clustered at the firm level in case that there may be autocorrelation of errors. Significance levels: 10% *, 5% **, and 1% ***.

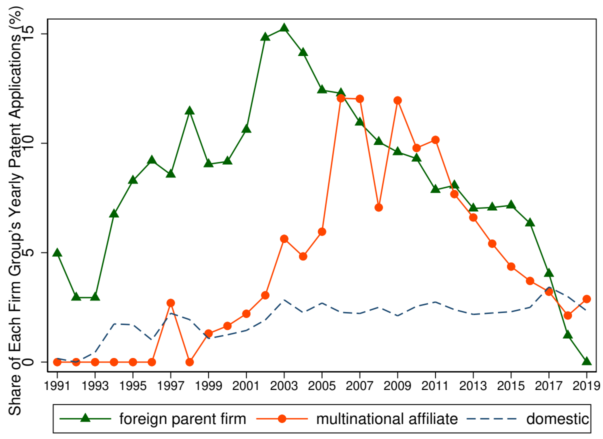
Table A.7: Association between Technology Spillovers and Domestic Firms' Technology

Dependent Variable	$\log(1+patent_{i,t})$		Innovation Status		$\log(sales_{i,t})$		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)
$FDI\_share_{s(i),t}$	-0.009	-0.005	-0.006	-0.010**	-0.198***	-0.210***	-0.246***	-0.259***	-0.360***	-0.382***
	(0.006)	(0.006)	(0.004)	(0.004)	(0.026)	(0.026)	(0.041)	(0.041)	(0.061)	(0.061)
$\log(1+fdi\_spillover_{i,t})$	0.037**	0.015	0.055***	-0.064**	0.118***	-0.155	0.097***	-0.062	0.138***	-0.100
	(0.018)	(0.054)	(0.012)	(0.032)	(0.022)	(0.125)	(0.026)	(0.060)	(0.040)	(0.090)
$\log(1+par\_spillover_{i,t})$	0.229***	0.472***	0.083**	0.520***	-0.107	0.540*	-0.138	0.307**	-0.201	0.467**
	(0.060)	(0.133)	(0.036)	(0.102)	(0.073)	(0.297)	(0.092)	(0.127)	(0.138)	(0.192)
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	1,396,013	1,396,013	1,396,013	1,396,013	1,385,263	1,385,263	994,872	994,872	989,881	989,881
R-squared	0.000	0.012	0.002	0.000	0.140	0.139	0.057	0.057	0.073	0.073
Instrument	ind shift	WTO	ind shift	WTO	ind shift	WTO	ind shift	WTO	ind shift	WTO
First-stage F	1147.05	179.01	1147.05	179.01	1150.17	96.70	1237.97	1711.82	1236.75	1712.16

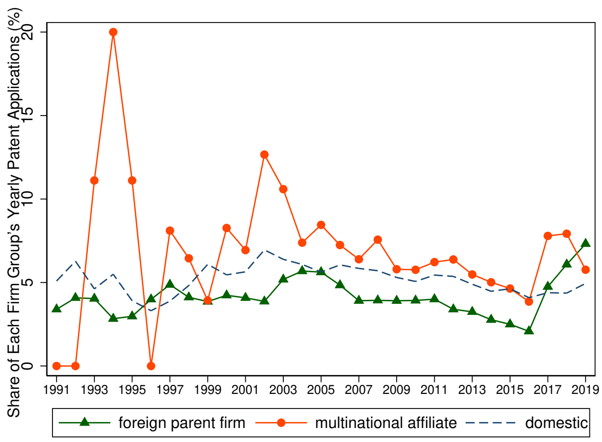
Notes: In this table, we replicate the regressions in Columns (3)–(4) of Table 4 with different dependent and independent variables. Firm-level controls include capital stock, employment, and dummies of firms' ownership structure (e.g., private or state-owned firms). We construct firm-year-level TFP 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, payroll, 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 $\frac{2}{3}$ 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). In constructing the second measure, because there are extensive labor distortions in China, we follow Hsieh and Klenow (2009) to proxy China's industry-level labor share using the corresponding industry-level measure from the US, and we consider the elasticity of demand substitution between firms within an industry is 3. Columns with odd numbers employ the instrument created in equation (6) (we analogously construct the instrument for spillovers from foreign parent firms). Columns with even numbers use the instrument constructed in equation (7) (we analogously construct the instrument for spillovers from foreign parent firms). $FDI\_share_{s(i),t}$ represents the share of multinational affiliates' sales in total industry-level sales for firm i's affiliated industry in year t. Standard errors are clustered at the firm level in case that there may be autocorrelation of errors. Significance levels: 10% *, 5% **, and 1% ***.



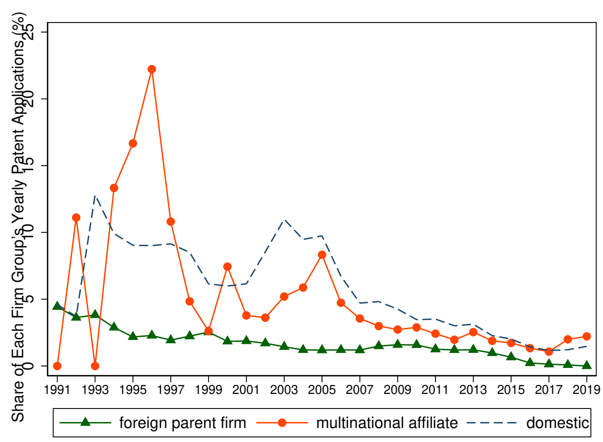
(a) Smart Phones



(b) Seminconductors



(c) Software



(d) Pharmaceuticals

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

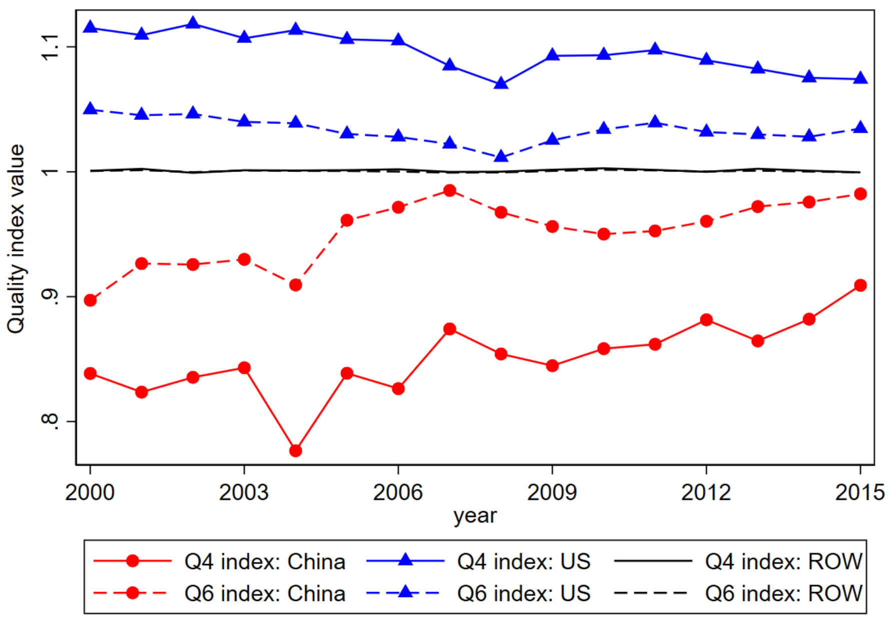


Figure A.2: Patent Quality Comparison

B Additional Results of Quantitative Model

B.1 Proof of Proposition 1

According to equation (16), we have:

$$\underbrace{p_1 A^i_{i,1}\phi(M^i_{i,1})^{\phi-1}(L^i_{i,1})^{1-\phi}}_{\text{marginal revenues of innovation}} = \underbrace{\frac{p_0 W_{i,0}}{A^e_{i,0}\psi(L^e_{i,0})^{\psi-1}\sum_{j'}\tau^{j'}_{i,0}q^{j'}_{i,0}M^{j'}_{i,0}}}_{\text{marginal costs of innovation}}.$$

Thus, we can solve $M^i_{i,1}$:

$$M^i_{i,1} = \left(\frac{p_0 W_{i,0}}{p_1\phi A^e_{i,0}A^i_{i,1}\psi(L^e_{i,0})^{\psi-1}\sum_{j'}\tau^{j'}_{i,0}q^{j'}_{i,0}M^{j'}_{i,0}}\right)^{1/(\phi-1)} L^i_{i,1}.$$

Given that $\phi < 1$, it is evident that the technology stock ($M^i_{i,1}$) of domestic firms will increase with the presence of spillovers ($\sum_{j'}\tau^{j'}_{i,0}q^{j'}_{i,0}M^{j'}_{i,0}$) and domestic firms' employment ($L^i_{i,1}$). Consequently, a higher level of spillovers would result in a greater technology stock for domestic firms ($M^i_{i,1}$). On the other hand, increased competition from multinational firms would lead to a reduction in employment within domestic firms ($L^i_{i,1}$), subsequently decreasing their technology stock ($M^i_{i,1}$).

B.2 Construction of Data Moments

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

Share of multinational firms' value added in China relative to China's GDP. We first use ASM 2000–2007 and find that multinational affiliates accounted for 12% of China's total manufacturing value added. 55% of multinational affiliates in China were in manufacturing, and manufacturing accounted for 32% of China's GDP. Because we do not have nonmanufacturing production value, we assume that compared with manufacturing multinational affiliates, each nonmanufacturing multinational affiliate represents an identical share of China's GDP. Based on this assumption, we compute $12\% \times \frac{32\%}{55\%} = 7\%$ as the share of multinational firms' value added in China relative to China's GDP.

Ratio of ROW's GDP to China's GDP. We directly use the Penn World Table to compute the ratio of ROW's GDP to China's GDP in the 2000–2015 period.

Employment-to-population ratio in China. We use the data on population and employment from China's Bureau of Statistics to compute this moment.

Number of ROW's patents relative to that of China's domestic patents. We obtain the amount of granted patents between 2000–2015 from the World Intellectual Property Organization (WIPO). Combining this with China's patent data, we can compute the number of ROW's patents relative to that of China's domestic patents.

Number of multinational affiliates' patents invented in China relative to that of China's domestic patents. Using the information we documented in Section 2.2, we can compute the number of multinational affiliates' patents invented in China relative to that of China's domestic patents.

Ratio of technology capital to GDP in China. We draw this moment directly from HMP. Technology capital in China includes both non-transferred technology capital (which is created by Chinese firms) and transferred capital (which is transferred from multinational firms).

Impact of multinationals' knowledge spillovers on China's patents. As it is difficult to interpret the regression results based on the logarithm of one plus the patent numbers, we rely on the coefficients in Appendix Table A.6, which are based on the levels of patent numbers and technology spillovers. We use the coefficient on $spillover_{i,t}$ in Column (4), which is based on the instrument capturing China's WTO accession, to compute the number of patent applications in the counterfactual scenario of no spillovers by setting $spillover_{i,t} = 0$. 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.

Annual share of multinationals' knowledge transferred to China. We note that in the steady state of our model, the share of multinationals' knowledge transferred to China relative to all the knowledge brought to China is:

$$\text{Share} = 1 - \frac{\delta_M}{1 - (1 - \delta_M)(1 - h_{\mathcal{C}}(q_{\mathcal{C}}^{\mathcal{R}}))}, \tag{18}$$

which is derived because the total amount of technology capital brought by multinationals is $\frac{\phi_{i,t}(L_{i,t}^{e};\widetilde{M}_t)+\phi_{j,t}^{i}(L_{j,t}^{i,e};\widetilde{M}_t)}{\delta_M}$ and the available amount of technology capital after technology transfers is $\frac{\phi_{i,t}(L_{i,t}^{e};\widetilde{M}_t)+\phi_{j,t}^{i}(L_{j,t}^{i,e};\widetilde{M}_t)}{1-(1-\delta_M)(1-h_{\mathcal{C}}(q_{\mathcal{C}}^{\mathcal{R}}))}$.

To back out $h_{\mathcal{C}}(q_{\mathcal{C}}^{\mathcal{R}}))$, we need to compute the share. We add up all the transfers and licenses from multinational affiliates and their foreign parent firms to domestic firms. We also consider that all the joint ventures' inventions are also transferred to China. Therefore, we totally have 63,419 patents that were transferred from multinational affiliates and their foreign parent firms to China in 2000–2015, which accounted for 13.3% of the total amount of the patents filed by multinational affiliates and their foreign parent firms in 2000–2015. Thus, we set the share to be 13.3%. With $\delta_M = 0.08$ in the baseline calibration, we obtain the annual share of multinationals' knowledge transferred to China $h_{\mathcal{C}}(q_{\mathcal{C}}^{\mathcal{R}})) = 0.013$.