The Local Technology Spillovers of Multinational Firms

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Abstract

This study investigates how innovation by multinational firms in the United States affects the productivity growth of domestic Chinese firms located in the same geographical areas as these U.S. multinationals' subsidiaries. Using firm-level data from both the United States and China, I manually match U.S. multinational firms with their manufacturing subsidiaries in China and use citation-weighted patent stocks to measure the stocks of external knowledge produced by U.S. multinational firms in the local areas in China where their subsidiaries locate. I also adopt an instrumental variable strategy based on U.S. R&D tax credit policies to address potential endogeneity concerns. I find that innovation by U.S. multinational firms improves the productivity of domestic Chinese firms co-located with the U.S. multinational firms' subsidiaries, indicating in a local technology spillover effect. Domestic firms with high-wage workers, high innovation capacity, and private ownership are more capable of absorbing the local technology spillovers. Finally, I find domestic firms in industries with closer technological ties to the U.S. multinational firms benefit more from these multinational firms' innovation than do domestic firms in less related industries, suggesting that technological proximity between the domestic firms and U.S. multinational firms amplifies the local technology spillovers.

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1. Introduction

The rapid expansion of multinational firms over the past several decades has been accompanied by a lengthy debate about their role in the global economy, particularly in developing countries. It has been argued that international knowledge spillovers through multinational business activities stimulate global economic growth and drive a convergence in productivity between developing and developed countries (Keller, 2004) through the transmission of technologies from multinational firms' home countries to developing countries. The hypothesis is supported by a body of macro-level empirical findings that foreign direct investment (FDI) is positively associated with GDP growth in developing countries (e.g., Borensztein et al., 1998). However, the micro-level evidence for technology spillovers driven by multinational activities remains mixed and inconclusive (Harrison and Rodríguez-Clare, 2010; Keller, 2021). Previous empirical studies of FDI spillovers typically measure spillover intensity based on multinational firms' relative size in domestic industries in terms of employment or sales. However, it is difficult for this approach to accurately reflect the extent of technological diffusion from multinational firms to domestic firms.[2] Another empirical challenge is to identify the causal impact of multinational activities on the performance of domestic firms, since FDI is endogenously correlated with the economic development in host countries (Keller, 2021).

Instead of investigating the consequences of multinational firms' expansion on domestic firms' performance, this paper sheds light on a previously understudied empirical question in the FDI spillover literature: does innovation by multinational firms in the home country result in technology spillovers to domestic firms co-located with the multinationals' subsidiaries in the host country?[3] In the context of this paper, I study the impact of innovation by

[2]On the one hand, horizontal FDI spillovers are often estimated to have neutral (Haddad and Harrison, 1993) or negative (Aitken and Harrison, 1999; Lu et al., 2017) effect on domestic firms' productivity growth because the size-based measures also entail intensification of competition from multinational firms (Haskel et al., 2007; Keller and Yeaple, 2009). On the other hand, vertical FDI spillovers (spillovers from FDI in the upstream or downstream sectors) are often found to improve domestic firms' performance (Javorcik, 2004; Javorcik and Spatareanu, 2008), but it is difficult to separate the effect of technology spillovers from the effect of supply or demand shocks on downstream or upstream industries following the expansion of multinational firms in host countries.

[3]It has been well established that knowledge spillovers, especially the diffusion of applied technologies, are

multinational firms in the United States, the most technologically advanced country, on the productivity growth of domestic firms in China, one of the world's fastest-growing economies, between 2000 and 2007. In particular, I build up a novel linkage between U.S. multinational firms and their subsidiaries in China, adopt an instrumental variable strategy based on U.S. R&D tax credit policies to address the endogeneity concerns frequently encountered in the previous FDI spillover studies, estimate the effect of U.S. multinational firms' innovation on productivity growth of domestic firms co-located with the multinational's subsidiaries, and investigate the determinants of local firms' absorptive capacity underlying the local technology spillovers of U.S. multinational firms.

As a first step, I manually construct a concordance between U.S. and Chinese firm-level data by matching U.S. multinational firms with their Chinese manufacturing subsidiaries based on annual financial reports (10-K files) of U.S. public companies. The resulting match accounts for more than 40% employment of U.S. multinational firms in China and includes some of the most technologically advanced multinationals in the early 2000s, such as General Electric, Cummins, and Procter&Gamble. I then study how changes in the aggregated citation-weighted patent stocks of U.S. multinational firms, as a measure of the external knowledge introduced by the U.S. multinational firms in the local areas of China, affect the productivity growth of the domestic firms operating within the same counties as the U.S. multinational subsidiaries.[4]

An ideal setting to identify the local spillover effects of multinational firms' innovation would be as follows. One could imagine, for example, both General Electric (GE) and Procter &

geographically localized (Henderson et al., 1993; Peri, 2005; Agrawal et al., 2008; Murata et al., 2014, among others). While previous FDI spillover studies generally focus on FDI spillover effects at the national level, I instead focus on how innovation by multinational firms affects the productivity growth of local domestic firms – firms within the same narrowly-defined geographic area (county) as the multinational subsidiary. In this respect, my study's focus on localized spillovers is similar to that of Greenstone et al. (2010), Setzler and Tintelnot (2021), and Abebe et al. (2022).

[4]In a similar fashion, Blit (2018) uses patent citation relationships between domestic firms and multinational firms to measure technology diffusion. I extend the scope of his study by relating the patent accumulation of multinational firms to the productivity growth of domestic firms to reveal the real effects of multinational innovation (Jones and Williams, 1998; Hall et al., 2010; Hall, 2011; Matray, 2021, among others).

Gamble (P&G) have established subsidiaries with similar characteristics in China, and an exogenous technology breakthrough takes place in P&G, while GE's technology remains the same. To identify the technology spillovers to domestic firms in China, one should compare the performance of domestic firms that are geographically close to P&G's subsidiary with those that are close to GE's subsidiary before and after the timing of P&G's breakthrough technology. The empirical challenge in practice is that any technology breakthrough by multinational firms are unlikely to be entirely exogenous, as some of the unobserved determinants of multinational firms' innovation may also be correlated with the performance of domestic firms in host countries. For instance, GE's financial difficulties over the past decade may have undermined its own innovation outputs as well as the performance of its domestic suppliers that co-locate with GE's subsidiaries in China.

To address these endogeneity issues, I construct an instrumental variable for the patent stocks of U.S. multinational firms based on U.S. state-level R&D tax credits, which are independently introduced and implemented by each state government and generate exogenous shocks to U.S. firms' innovation (Wilson, 2009; Bloom et al., 2013). This instrumental variable strategy allows me to compare domestic Chinese firms co-located with multinational subsidiaries whose U.S. parent firms enjoy high exogenous R&D incentives with those co-located with multinational subsidiaries whose parent firms are subject to low R&D incentives provided by the government. I further demonstrate that changes in R&D tax credits during the sample period are unrelated to either *ex-ante* local economic development in China or Chinese import competition shocks (Autor et al., 2013), suggesting that the identification strategy is unlikely to violate the exclusion restrictions.

This R&D tax credit policy-based IV strategy yields two main findings. First, innovation by U.S. multinational firms improves the productivity of domestic Chinese firms located in the same counties as the multinationals' subsidiaries, indicating a local technology spillover effect from U.S. multinational firms to local domestic firms in China. The technology spillover effect is highly localized, as the effect only extends to domestic firms in counties within a radius of no more than ten kilometers of multinational subsidiaries. Second, the local spillover effect is contingent on the absorptive capacity of the domestic firms (Cohen and Levinthal, 1990). Firms with high-wage workers, high innovation capacity, and private ownership exhibit stronger productivity gains in response to innovation by U.S. multinational firms. The technological proximity of domestic industries to the multinational firms' innovation also plays an important role in channeling local spillovers, as local domestic firms in industries with closer technological ties to U.S. multinational firms experience more substantial productivity gains following innovation by the multinational firms.[5]

The paper's contribution is twofold. First, unlike the size-based measures commonly used in the literature on FDI spillovers (Aitken and Harrison, 1999; Javorcik, 2004; Lu et al., 2017), the patent-based measure of multinational firms' local presence based on firm-to-firm linkages allows me to improve measurement quality of FDI spillovers by isolating the technology-related components of multinational activities.[6] This approach also echoes the call for more accurate measures of multinational firms' technological knowledge and innovation in the FDI spillover literature (Keller, 2021). Second, the IV strategy based on the U.S. R&D tax credit policies improves on both the conventional and the more recent identification methods used in the FDI spillover literature. Early FDI spillover studies, such as Haddad and Harrison (1993); Aitken and Harrison (1999); Javorcik (2004), mostly rely on fixed effects models, which primarily reveal correlations between FDI activities and domestic firms' productivity growth. Some more recent studies in the field provide causal evidence of FDI spillovers, but their strategies are mainly based on policy changes in the host countries. For example, Lu et al. (2017) exploit the relaxation of FDI restrictions in China, and Abebe et al. (2022) examine exogenous variations in multinational firms' location choices in Ethiopia. This paper introduces a new way of identifying multinational firms' technology spillovers by exploiting exogenous policy shocks in the origin country of FDI. While policies in the host countries may be affected by the local economic development in those countries (which are

[5] The finding echoes with Bloom et al. (2013), which finds that technological proximity plays an essential role in technology spillovers in the U.S.

[6] One recent example that exploits firm-to-firm linked data is Alfaro-Urena et al. (2022), which utilizes firm-to-firm transaction data to examine the effect of joining multinational supply chains on domestic firms' employment and total factor productivity (TFP).

also likely to affect domestic firms' performance), this paper overcomes such challenges by adopting an identification strategy based on policies in a multinational's home country.[7]

The remainder of the paper is organized as follows. Section 2 introduces the data and constructs the key variables. Section 3 outlines the main specifications and introduces the identification strategy. Section 4 presents the baseline results and related robustness checks. Section 5 examines the determinants of local firms' absorptive capacity. Section 6 concludes the paper.

2. Data and Variable Construction

2.1. Institutional Backgrounds

The Chinese economic reform starting at 1978 aimed to transform the central-government-planned economy into a market economy. In 1980, the Chinese government began to gradually open the economy to international trade and foreign investment, resulting in the steady growth of multinational activities. After China joined the World Trade Organization (WTO) in 2001, the net inflow of FDI to China skyrocketed, growing from less than US$50 billion in 2001 to about US$250 billion in 2010.

U.S. multinational firms became active in China in the early phases of China's market reform. The U.S. and the People's Republic of China established diplomatic relations in 1979. In the following years, numerous U.S. multinational firms established their first subsidiaries in China, including Coca-Cola (1979), Pepsi (1981), Johnson & Johnson (1982), and Hewlett-Packard (1985). Although these early entrants often opted for headquarters in major cities such as Beijing, Shanghai, and Guangzhou, they later expanded operations to other cities. For example, Pepsi first established its headquarter in Beijing in 1981. By 2000, however, the

[7]A closely related paper by Blit (2018) identifies the technology spillover effect of FDI by comparing patent citations made by domestic firms to multinational firms before and after the entry of multinational subsidiaries into the host country. However, this strategy cannot eliminate the possibility that multinational firms may self-select into countries where relevant technologies are already being implemented (for example, GE might establish subsidiaries in countries where the electronics industry is already booming). This paper improves on the approach of Blit (2018) by focusing on established multinational subsidiaries and by exploiting the subsequent exogenous policy shocks that may affect the innovation of their parent firms.

company had established multiple factories in regional centers such as Changchun, Chengdu, Chongqing, Guilin, Nanchang, and Nanjing. The surge in investment by U.S. multinational firms after China's accession to the WTO led the U.S. to become the third-largest source country of FDI in China by 2006, following Japan and South Korea.

2.2. Data Sources and Variable Construction

The Chinese data used in this study come from the Annual Survey of Industrial Enterprises (ASIE), which is administered by the Chinese National Bureau of Statistics (NBS) and includes all SOEs and non-SOEs with annual sales of over 5 million Chinese yuan (about US $604,600 in 2000). The data contain basic business information for each firm, including name, location, industry, ownership type, and year of establishment. The data also include operational outcomes, such as gross output, value-added output, fixed assets, intermediate inputs, and employment.[8] I primarily focus on two measures of productivity as outcome variables: total factor productivity (TFP) and labor productivity. In line with Levinsohn and Petrin (2003), I estimate TFP based on a three-factor production function with gross revenue as the production output and employment, capital, and intermediate inputs as production inputs.[9] Labor productivity is measured using the log value-added output per worker. Other Chinese data sources used in this study include data on Chinese patents from the State Intellectual Property Office (SIPO), which contains information on the patents granted to individuals and firms by the SIPO between 1990 and 2015[10] and the GIS data for the 2000 administrative boundary map of China provided by the NBS.

The U.S. data sources include patent data from the Harvard Patent Network Dataverse, which are primarily collected from the U.S. Patent and Trademark Office (USPTO). The data encompass all patents granted in the U.S. from 1975 to 2010. They contain information for each patent applicant, including name, state, and assignee number; as well as the characteristics of each patent, including technology classification, application year, and grant year.

[8]The definition and treatment of each variable are listed in Appendix C.

[9]Following Brandt et al. (2017), I construct capital stocks using the perpetual inventory method. The detailed TFP estimation procedure is outlined in Appendix D.

[10]These patent data are widely used in similar studies, such as Bombardini et al. (2017). I use the matched ASIE-SIPO data compiled by He et al. (2018).

The data also cover every pair of cited and citing patents. I use the crosswalk by Autor et al. (2020) to link each patent to the publicly listed firms in the U.S. I then extract financial and operational information of the public firms from the Compustat database.

2.3. Matching U.S. Multinational Firms to their Chinese Subsidiaries

Recent economics, finance, and accounting research increasingly exploits the textual data in firms' financial reports to collect unreported information in the financial statements. For example, Dyreng and Lindsey (2009) use subsidiary lists in 10-K files to study how tax havens affect multinational firms' tax rates, and Hoberg and Moon (2017) and Hoberg and Moon (2019) compile textual data in 10-K files to examine U.S. firms' exposure to off-shoring activities.[11] This study expands on previous approaches by extracting exact parent-subsidiary information from 10-K filings. Instead of using confidential data sources that directly identify parent-subsidiary relationships,[12] I directly identify the parent-subsidiary relationships based on publicly accessible financial reports that allow me to combine rich firm-level panel data from both the U.S. and China.

Matching U.S. public multinational firms with their Chinese subsidiaries involves both automated textual search algorithms and manual matching. I use the annual 10-K filings from the Securities and Exchange Commission (SEC) database to construct these relationships. I first download all 10-K filings from the SEC Edgar database and then use text scraping to identify U.S. firms that mention a given set of keywords[13] in their 10-K filings. I conduct a validation check with around 50 financial reports to confirm that the search algorithm can identify firms with various forms of operations in China.

[11] Other related studies include Hoberg and Phillips (2010) and Hoberg and Phillips (2016), which construct 10K-based product similarity measures; Loughran and McDonald (2011), which construct 10K-based measures of tones; and Bodnaruk et al. (2015), which constructs a 10K-based measure of financial constraints.

[12] For example, Branstetter et al. (2006), Keller and Yeaple (2013), and Bilir and Morales (2020) use within-firm transaction records obtained from the U.S. Bureau of Economic Analysis (BEA); Jiang et al. (2018) uses the Name List of Foreign and Domestic Joint Ventures in China from the Chinese Ministry of Commerce.

[13] The keywords are any combinations of "China" or "Chinese" and "subsidiary (subsidiaries)," "operation," "facility (facilities)," "investment," or "venture" in the same sentence.

Of the resulting 1,148 candidate firms identified, I extract and manually examine the "Exhibit 21: List of Subsidiaries" tables in their 10-K filings to identify the exact names and locations of their Chinese subsidiaries, if they exist.[14] For financial reports where Exhibit 21 tables are missing or do not contain explicit information on Chinese subsidiaries, I examine the main text of the 10-K filings to search for related keywords and record the exact nature of these firms' operations in China. I then manually match these subsidiaries with the ASIE data. After excluding sales offices, representatives, or business partners, a large proportion of the affiliates listed in the 10-K files, I match 224 U.S. public firms with 410 above-scale manufacturing subsidiaries from the ASIE data. Supplementing the list of subsidiaries from the 10-Ks with an additional list of U.S. subsidiaries in China from the ORBIS database identifies 11 more U.S. public firms and 42 more subsidiaries, which suggests that the 10-K-based method of identifying Chinese subsidiaries of U.S. public firms indeed captures a major proportion of U.S. multinational ownership linkages. The sample is then restricted to parents and subsidiaries established in or before 2000 to eliminate endogenous entry problems. Finally, I match the U.S. multinational firms with the patent data, which reduces the sample to 171 U.S. public firms and 334 matched Chinese subsidiaries. Although the final sample contains a limited number of U.S. multinational firms and subsidiaries, the total number of workers employed at the matched subsidiaries exceeded $130,000$ in 2000, a substantial proportion of the $292,600$ total employees of all non-bank U.S. foreign affiliates in China in 2000 (according to the BEA).[15]

2.4. U.S. Multinational Firms' Patent Stocks

The study uses the patent stocks of U.S. firms to measure the accumulation of external knowledge produced by U.S. multinational firms in local areas of China. I first match the patent records from the Harvard Patent Dataverse with Compustat public firms using the crosswalk provided by Autor et al. (2020). I then calculate each firm's citation-weighted

[14] Dyreng and Lindsey (2009) also use Exhibit 21 tables to identify multinational firms' foreign operations, although their study only utilizes country information.

[15] A detailed description of the name-matching procedure (with the example of Pepsi Co.) and a discussion of the matching outcomes are outlined in Appendix B.

patent counts based on the citation records.[16] I apply the perpetual inventory method to compute each firm's citation-weighted patent stocks:

$$PatStock_{mt} = (1 - \eta)PatStock_{mt-1} + Pat_{mt}, \tag{1}$$

in which m denotes each U.S. multinational firm and t denotes each year from 1975 to 2010. $PatStock_{mt}$ is multinational firm m's cumulative patent stock in application year t, and Pat_{mt} is m's citation-weighted count of patents in application year t. The depreciation rate, η, is set at 0.15, as is common in the literature (Hall et al., 2005; Matray, 2021).

To measure the stocks of foreign technological knowledge from U.S. multinational firms in each Chinese county, I compute a weighted sum of patent stocks of the U.S. multinational firms whose subsidiaries are located in the county:

$$PatStock_{ct}^{loc} = \sum_{j \in J(c)} PatStock_{m(j)t} \cdot \frac{emp_0(j)}{total\_emp_0(c)}, \tag{2}$$

where c denotes each Chinese county, j denotes a matched U.S. subsidiary, and $m(j)$ denotes the parent of subsidiary j. $J(c)$ is the set of all matched U.S. subsidiaries in county c, $PatStock_{m(j)t}$ is j's parent multinational $m(j)$'s patent stock at year t, $emp_0(j)$ is the initial employment of subsidiary j, and $total\_emp_0(c)$ is the total initial employment of ASIE firms in county c.[17] The aggregated county-level patent stock of U.S. multinational firms, $PatStock_{ct}^{loc}$, is a weighted sum of each U.S. multinational's patent stock, where the weights are the initial employment share of each subsidiary in the local economy, $emp_0(j)/total\_emp_0(c)$. I use time-invariant weights to avoid potential endogeneity problems arising from technology-induced changes in subsidiary employment shares. The local patent stock measure is consistent with the intuition that local technology spillovers from multinational firms are facilitated by the movement of high-skilled workers from the multinational subsidiaries to domestic firms (Poole, 2013; Setzler and Tintelnot, 2021). An average do-

[16] To address the truncation problem, I implement the quasi-structural approach proposed in Hall et al. (2001) and Hall et al. (2005) to adjust the patent counts.

[17] A firm's initial year is defined as the first year when the firm appears in the data, and its initial employment is calculated as the firm's employment in the initial year, deflated by the ratio of two-digit industry average employment in the initial year to the two-digit industry average employment in 2000.

mestic firm's exposure to each subsidiary's technology spillover is therefore proportional to the technology stocks of the multinational parent and the relative size of the subsidiary in the local economy. In the empirical analysis, I use the three-year lagged log local patent stocks as a proxy for the strength of local technology spillovers to account for the duration of technology sharing between parent companies and subsidiaries and the learning period of local domestic firms.[18]

Figure 1 exhibits the geographic distribution of $ln(PatStock^{loc})$ in 2000. A majority of innovation-intensive multinational firms are concentrated around the four largest cities, Beijing, Shanghai, Guangzhou, and Shenzhen, as well as the most developed provinces, such as Guangdong, Zhejiang, and Jiangsu. The other multinational subsidiaries are dispersed throughout the country. Some subsidiaries of the most innovative U.S. multinational firms are also located in less developed parts of China, such as the northeast, southwest, and central regions.

By construction, the $PatStock^{loc}$ measure is constant across all domestic firms located within the same county and thus only captures the general impact of multinational technology stocks in the local area. In reality, some domestic firms, especially those specializing in the technology fields of U.S. multinational firms' innovation, may accumulate a greater amount of technical expertise that enable them to appropriate the technological knowledge of U.S. multinational firms more effectively. To gauge the extent of spillovers through such technological linkages, I construct a location-by-industry-level measure of local patent stocks of U.S. multinationals based on the similarities between the types of innovation multinationals carry out and domestic industries' patent profiles. I first compute each multinational firm's patent stocks in each International Patent Classification (IPC) subclass.[19] A U.S. multinational firm m's patent stocks in all IPC subclasses in year t can be expressed as a vector

[18] As shown in Figure A1, my baseline findings are robust to alternative lagged-year choices, while spillover measures in lead years have no effect on domestic firms' productivity.

[19] There are around 600 total subclasses in the IPC system.

Figure 1: Geographic distribution of $\ln \left(PatStock^{loc} \right)$ in 2000

Notes: The figure shows the geographic distribution of the county-level patent stocks of U.S. multinational firms in China, which is the three-year lagged log weighted sum of the multinational firms' citation-weighted patent stocks. The subsidiaries are located in 125 of 2,280 Chinese counties.

$\overrightarrow{PatStock}_{mt}^{subclass} = (PatStock_{mt}^{1}, PatStock_{mt}^{2}, ..., PatStock_{mt}^{\mathbb{T}})$, where $PatStock_{it}^{\tau}$ denotes firm i's patent stock in IPC subclass τ in year t. Next, using the ASIE-SIPO merged data, I compute the percentages of total invention patent applications by domestic firms between 2000 to 2007 in each IPC subclass for each 4-digit Chinese industry n: $\vec{p}_n = (p_n^1, p_n^2, ..., p_n^{\mathbb{T}})$, where p_n^{τ} denotes the share of patents in IPC subclass τ in the total number of patents of a 4-digit industry n. Last, I compute a technological proximity-based measure of U.S. multinational firms' patent stocks in industry n and county c:

$$\begin{aligned} PatStock_{nct}^{prox} &= \sum_{j \in J(c)} (\overrightarrow{PatStock}_{m(j)t}^{subclass} \cdot \vec{p}_n) \frac{emp_0(j)}{total\_emp_0(c)} \\ &= \sum_{j \in J(c)} \sum_{\tau \in \{1,2,...,\mathbb{T}\}} p_n^{\tau} PatStock_{m(j)t}^{\tau} \frac{emp_0(j)}{total\_emp_0(c)}, \end{aligned} \tag{3}$$

I demonstrate the intuition behind the technological proximity-based measure, $PatStock^{prox}$, with a simple example. Television manufacturing in China heavily depends on electrical and electronic technologies, especially those on digital signal transmission. It is highly likely that innovation by Motorola, once one of the largest multinational firms in China and a specialist in digital signal technologies, will substantially benefit a domestic television manufacturer in the local area. In contrast, the technologies developed by P&G are unlikely to benefit domestic television manufacturers because very few of P&G's technologies are applicable to the production of televisions. The difference between the local spillover effects of Motorola's and P&G's technologies on the local television producers will be reflected in $PatStock^{prox}$, which is substantially larger for television manufacturers in counties with Motorola subsidiaries than those in counties with P&G subsidiaries.

2.5. Summary Statistics

Table 1: Summary statistics

	Mean	Std. Dev.	25 Percentile	Median	75 Percentile	Observations
Panel A. Matched subsidiaries						
	Mean	Std. Dev.	25 Percentile	Median	75 Percentile	Observations
Gross output (millions RMB)	676.19	3832.23	66.44	162.86	393.32	1988
Value added (millions RMB)	200.97	1120.48	15.59	47.41	125.77	1988
Employment	512.33	1128.76	88.00	201.50	501.00	1988
Wage (thousands RMB)	53.47	217.83	22.31	37.64	63.25	1988
$TFP-LP$	-0.82	1.74	-1.15	-0.52	0.04	1988
Labor productivity	12.03	1.89	11.38	12.29	13.12	1988
Wholly foreign ownership (%)	0.50					1988
Panel B. Domestic firms in matched counties						
	Mean	Std. Dev.	25 Percentile	Median	75 Percentile	Observations
Gross output (millions RMB)	68.06	747.53	8.60	16.42	37.39	221923
Value added (millions RMB)	17.75	225.94	1.88	4.02	9.62	221923
Employment	200.93	640.86	45.00	86.00	175.00	221923
Wage (thousands RMB)	15.77	47.68	9.29	12.20	17.26	221923
$TFP-LP$	-1.16	1.38	-1.59	-1.01	-0.51	221923
Labor productivity	10.61	1.51	10.07	10.71	11.41	221923
State ownership (%)	0.21					221923
Collective ownership (%)	0.20					221923
Private ownership (%)	0.59					221923
Panel C. Patent stock measures						
	Mean	Std. Dev.	25 Percentile	Median	75 Percentile	Observations
$ln(PatStock)$	7.53	2.56	6.54	7.85	9.23	1988
$ln(PatStock^{loc})$	2.63	3.28	1.02	2.89	5.20	221923
$ln(PatStock^{prox})$	-3.10	3.44	-4.91	-2.75	-0.57	211221

Notes: This table presents the summary statistics for the key variables in the analysis. Panel A presents the characteristics of the matched subsidiaries, Panel B presents the characteristics of the domestic firms in the matched counties, and Panel C presents the distribution of the multinational technology stock measures. The units are noted in parentheses, if necessary.

Table 1 displays the summary statistics for the key variables in the analysis. Panel A includes the sample of all matched subsidiaries of the U.S. public multinational firms, and Panel B includes the sample of all domestic firms in the 125 matched Chinese counties. Panel C presents the distribution of the patent stock measures. A comparison of Panel A and Panel B demonstrates that the matched U.S. subsidiaries are larger in size and more productive than domestic Chinese firms. On average, the matched subsidiaries have 994% of the sales of domestic firms, 255% of the employment of domestic firms, and 40.5% higher TFP than domestic firms. An average U.S. subsidiary also pays 239% higher wages to its employees. The significant differences between the subsidiaries and domestic firms indicate that U.S. multinational firms are substantially more technologically advanced than domestic firms, which may lead to sizable local technology spillovers.

3. Specification and Identification Strategy

3.1. Specification

My main analysis exploits fixed effects models to study the effect of multinational firms' innovation on the domestic firms' productivity:

$$Y_{it} = \beta^{loc} \ln(PatStock^{loc}_{c(i)t-3}) + f_i + f_{n(i)t} + f_{o(i)t} + \epsilon_{it}, \tag{4}$$

where i denotes each domestic firm, $c(i)$ denotes the county in which i is located, and t denotes each year from 2000 to 2007. Y_{it} represents the productivity measures (TFP and labor productivity) of i in year t, and $\ln(PatStock^{loc}_{c(i)t})$ is the natural logarithm of county-level aggregated patent stocks of U.S. multinational firms in year $t-3$, constructed in Equation 2. The regression equation controls for firm fixed effects f_i, 4-digit Chinese industry-by-year fixed effects $f_{n(i)t}$, and ownership type-by-year fixed effects $f_{o(i)t}$ to control for each firm's time-invariant characteristics, industry-specific fluctuations, and ownership type-specific time-varying fluctuations, respectively. In an extended variation, I control for potential time-varying effects of initial county characteristics by including the initial median TFP and the log value-added output of county $c(i)$ interacted with time dummies. The regression estimation is weighted using the initial employment of the domestic firms to control for heteroskedasticity in initial firm size (Greenstone et al., 2010).

The coefficient of interest is β^{loc}, which represents the local domestic firms' responses to the accumulation of foreign technology in each county. A positive β^{loc} indicates that innovation by U.S. multinational firms enhances the productivity growth of domestic firms located within the same county as the U.S. multinational firms' subsidiaries.

The ordinary least squares (OLS) estimates of Equation 4 may suffer from several endogeneity problems. The first potential problem is omitted variable bias, which may occur when innovation by multinational firms affects local firms in China via unobserved channels. The global development of automation technologies, for example, may stimulate the innovation of both U.S. multinational firms and multinational firms from other countries. Global co-movement of innovation may introduce a positive bias in the estimates, since domestic firms' productivity growth is also affected by unobserved technology spillovers from non-US multinational firms that are correlated with US multinational firms' innovation. There may also be an omitted variable bias issue caused by the self-selection of U.S. multinational firms into Chinese counties. For example, more innovative U.S. multinational firms may be able to bargain with the local governments of more developed regions to establish their subsidiaries. Consequently, the OLS estimate of Equation 4 contains a positive bias if the subsidiaries of the most innovative U.S. multinational firms are clustered in the fastest-growing regions of China. A second potential endogeneity problem may involve reverse causality or simultaneity (Manski, 1993). The innovation performance of U.S. multinational firms may instead be affected by the performance of Chinese domestic firms. A U.S. multinational firm may gain a competitive advantage when its local competitors in China perform poorly, affecting the multinational firm's innovation decisions. Such reverse causality results in a negative bias in the OLS estimates of Equation 4.

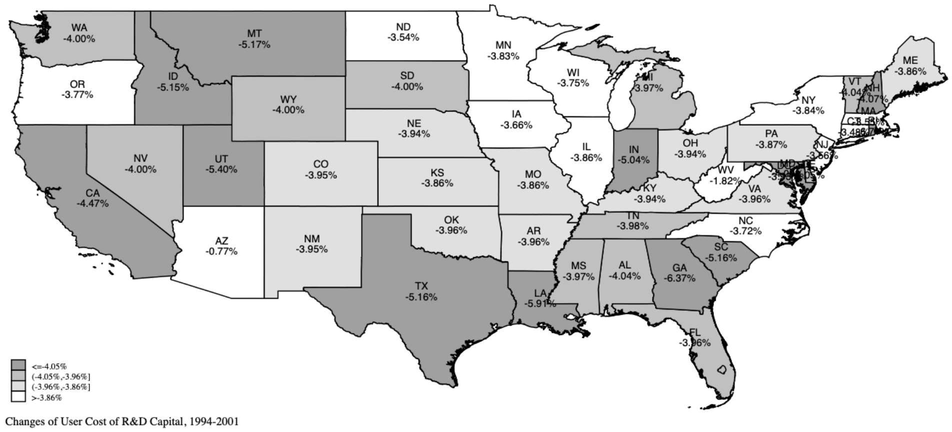
In the following section, I introduce an instrumental variable strategy based on the U.S.'s R&D tax credit policies to address these potential endogeneity problems.

3.2. The U.S. R&D Tax Credit

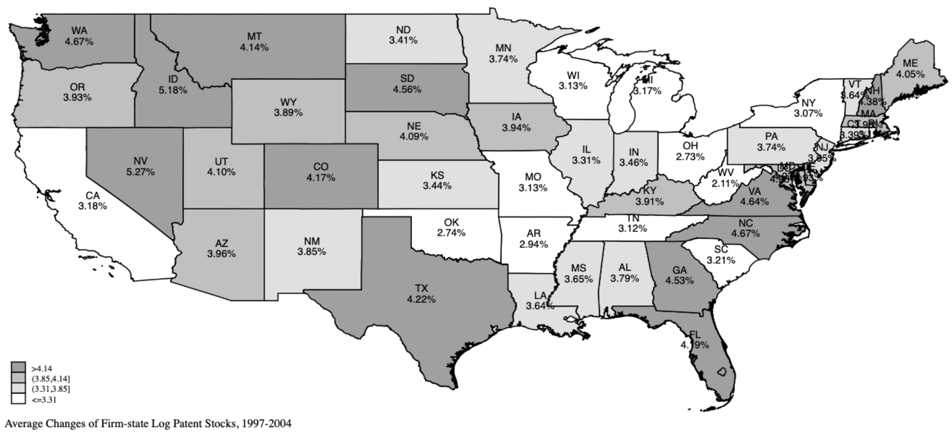
The U.S. research and experimentation tax credit, or the R&D tax credit, consists of two components: a federal tax credit and a state tax credit. The federal R&D tax credit was first introduced in the *Economic Recovery Tax Act of 1981*. The Act grants a 25% tax credit for all qualified research and development expenses (QRE) defined under the U.S. Internal Revenue Code (IRC).[20] Congress made the federal R&D tax credit permanent in 2015.

Figure 2: Changes in R&D Capital User Cost and Log Patent Stock

Panel A: Changes in R&D Capital User Costs



Panel B: Average Change in Log Patent Stock (Citation-weighted)



Notes: The figures show the geographic distribution of the changes in the R&D capital user cost and patent stocks of public U.S. firms. Panel A shows the change in the R&D capital user cost from 1994 to 2001, and Panel B shows the change in the median firm–state log patent stock from 1997 to 2004.

In 1982, Minnesota became the first state to introduce a state R&D tax credit. Several state governments have since introduced similar policies, typically following the federal government's definition of QRE. By 2007, 32 U.S. states had introduced some form of R&D tax

[20] As specified in section 41 of the 2005 IRC, the three main components of eligible research expenses are wages, supplies, and contract research expenses. Please see Audit Techniques Guide: Credit for Increasing Research Activities for detailed information.

credit. Hawaii, Rhode Island, Nebraska, California, and Arizona are among the states with the highest R&D tax credit rates, ranging from 11% to 20%.

The effectiveness of R&D tax credit policies hinges on macroeconomic conditions and federal government policies, such as interest rate fluctuations and corporate income tax adjustments. Following Hall (1992), Wilson (2009), and Bloom et al. (2013), my instrumental variable strategy relies on the state-specific, R&D tax credit-induced user cost of R&D capital (henceforth, the user cost of R&D capital) which incorporates the macroeconomic and federal policy factors.[21] As shown in Panel A of Figure 2, changes in the user cost of R&D capital varied significantly among states from 1994 to 2001, the years included in the empirical analysis. Furthermore, Panel B of Figure 2 shows that innovation activities grew faster in states that underwent larger reductions in R&D capital user costs, such as Texas and Georgia.

3.3. Instrumental Variable Construction

I construct the instrumental variables for the local U.S. multinational firms' patent stocks, $PatStock^{loc}$, through the following steps. First, using the full sample of firm–state–year observations,[22] I estimate

$$lnPat_{mst} = \lambda \rho_{st-3} + f_{ms} + f_t + \alpha_m t + \alpha_s t + \nu_{mst}, \tag{5}$$

where m denotes each public U.S. firm, s denotes each state, and t denotes each year from 1975 to 2010. Pat_{mst} is the citation-weighted patent counts by inventors in firm m located in state s in year t, and ρ_{st-3} is the user cost of R&D capital for the firms with the most R&D spending in state s and year $t-3$. The equation controls for firm-by-state fixed effects f_{ms}, year fixed effects f_t, and firm-specific and state-specific linear trends $\alpha_m t$ and $\alpha_s t$. The key coefficient, λ, represents the elasticity of the public firms' patent counts in response to the lagged user costs of R&D capital in each state.

[21] Appendix E presents the detailed formula for user cost of R&D capital.

[22] The panel data are filled to include missing observations. I apply $\ln(\min(x) + x)$ to the dependent variable to account for zero values.

Based on the estimated elasticity term $\hat{\lambda}$, I then compute the predicted patent counts at the firm-state level as:

$$\widehat{Pat}_{mst} = \exp(\hat{\lambda}\rho_{st-3}). \tag{6}$$

It is noteworthy that the variations in the predicted value of the patent counts solely result from differences in the state-specific user costs of R&D capital. After aggregating the predicted counts of patent applications at the firm level, I calculate the predicted patent stocks using the perpetual inventory method:

$$\widehat{PatStock}_{mt} = (1-\eta)\widehat{PatStock}_{mt-1} + \widehat{Pat}_{mt}, \tag{7}$$

where η is again set at 0.15. As in Equation 2, I compute the Chinese county-level predicted patent stocks of U.S. multinational firms as follows:

$$\widehat{PatStock}^{loc}_{ct} = \sum_{j \in J(c)} \widehat{PatStock}_{m(j)t} \cdot \frac{emp_0(j)}{total\_emp_0(c)} \tag{8}$$

The natural logarithm of the 3-year lagged Chinese county-level predicted patent stocks, $\ln(\widehat{PatStock}^{loc}_{ct-3})$, is used as the instrument for $\ln(PatStock^{loc}_{c(i)t-3})$ in Equation 4.[23]

Table 2 presents the estimation results of Equation 5 and the relationship between the actual patent stocks and predicted patent stocks at both the multinational–subsidiary level and the Chinese county level. Panel A estimates variants of Equation 5 in which the dependent variables in Columns 1 and 2 are natural logs of simple patent counts and the dependent variables in Columns 3 and 4 are natural logs of citation-weighted patent counts. Firm-specific and state-specific year trends are controlled in Columns 2 and 4. The estimates indicate that a 5% reduction in the user cost of R&D capital, similar to the actual reduction of R&D capital user cost in Texas from 1994 to 2001, improves an average firm's patent counts by 8.7% in simple terms and 17.4% in citation-weighted terms in the state. I set $\hat{\lambda} = -3.491$ (the estimate of λ in Column 4) to construct the predicted patent counts and

[23]Following similar steps, I also construct county–industry-level predicted patent stocks, $\widehat{PatStock}^{prox}_{nct}$, to instrument for $PatStock^{prox}_{nct}$. Table A1 shows that the user cost of R&D capital also has a strong negative effect on patenting at the firm-state-IPC subclass level.

patent stocks in Equation 6 and 7.

Table 2: First-stage Regressions

Panel A. U.S. firm-state level regressions				
Dependent variable	$ln(SimpleCounts)$		$ln(CitationWeightedCounts)$	
	(1a)	(2a)	(3a)	(4a)
ρ^h_{t-3}	-1.664***	-1.738***	-1.794**	-3.491***
	(0.437)	(0.667)	(0.830)	(1.318)
Firm-state fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm-specific year trends	No	Yes	No	Yes
State-specific year trends	No	Yes	No	Yes
Observations	494639	494639	494639	494639

Panel B. first stage regressions				
Dependent variable	$ln(PatStock^{mnc})$		$ln(PatStock^{loc})$	
	(1b)	(2b)	(3b)	(4b)
$ln(\widehat{PatStock}^{mnc})$	6.243***	6.238***		
	(0.984)	(0.977)		
$ln(\widehat{PatStock}^{loc})$			2.164***	2.158***
			(0.476)	(0.478)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Ownership-year fixed effects	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	1988	1988	221923	221923

Notes: Panel A presents the regression results for Equation 5. Panel B presents the estimated relationship between patent stocks and predicted patent stocks at both the multinational–subsidiary level and the Chinese county level. Regressions in Panel B are weighted using the adjusted initial employment of the firms. Robust standard errors are clustered at the state-by-year level in Panel A, the parent-firm level in Columns 1 and 2 of Panel B, and the Chinese county level in Columns 3 and 4 of Panel B. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Columns 1 and 2 of Panel B estimate the relationship between the log of multinational firms' patent stocks, $\ln(PatStock_{mt})$, and the natural log of the predicted patent stocks, $\ln(\widehat{PatStock}_{mt})$, at the multinational–subsidiary level. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in both columns, and Column 2 also controls for the median TFP and the log of value added output of domestic firms within the same counties as the subsidiaries.[24] Columns 3 and 4 estimate the first-stage regressions

[24]Columns 1 and 2 are the first-stage regressions of Table A2.

of the baseline specification, Equation 4, in which Column 4 futher controls for county-level initial median TFP and log value-added output interacted with year dummies. The results of Panel B indicate strong positive relationships between the actual patent stocks and predicted patent stocks at both the multinational–subsidiary level and the Chinese county level.

My identification strategy addresses the potential omitted variable bias and reverse causality problems previously discussed.[25] To address potential omitted variable bias, I first demonstrate that U.S. R&D tax credit policies have little impact on patenting by non-U.S. applicants in the European Patent Office (EPO) and the Japan Patent Office (JPO). This suggests that the IV estimates are unlikely to be biased by unobserved spillovers from non-U.S. subsidiaries caused by U.S. R&D tax credit policies. A set of placebo tests also show that the ex-post changes in instrumental variables are not correlated with ex-ante economic conditions and trends in domestic firms' performance, indicating that the location choices of multinational subsidiaries are unlikely to be correlated with the R&D tax credits received by their parent companies.[26] To address potential reverse causality issues, I demonstrate that the R&D tax credit policies are not correlated with Chinese import competition shocks (Autor et al., 2013), indicating that the U.S. R&D tax credit policies are unlikely to be reversely driven by Chinese economic shocks to the U.S.[27]

4. Main Findings

4.1. The Effect of U.S. Multinational Firms' Innovation on Local Firms' Productivity

Following the specification in Equation 4, I examine how changes in multinational firms' patent stocks affect the productivity growth of domestic firms located within the same coun-

[25] The detailed discussion of how the identification strategy fulfills the exclusion restriction criteria is outlined in Appendix E.

[26] Figure A2 exhibits results of event study analysis that regresses the TFP of local firms on the growth of U.S. multinational firms' patent stocks from 2000 to 2007 interacted with year dummies. The estimated event study coefficients show no evident patterns of preexisting trends, which again suggests that assortative matching between multinational subsidiaries and Chinese counties is unlikely.

[27] I further show that my identification strategy, which is similar to a shift-share design, is valid under the exposure-robust inference (Borusyak et al., 2022). Last, I demonstrate that my results are robust to an alternative instrumental variable construction, in which I first compute a firm-level weighted average user cost for R&D capital and then generate predicted patent stocks based on the firm-level relationship between patent applications and R&D capital user costs.

ties as the multinational subsidiaries in Table 3.[28] The dependent variable in Columns 1, 2, and 3 is TFP, estimated following Levinsohn and Petrin (2003). The dependent variable in Columns 4, 5, and 6 is labor productivity. Columns 1 and 4 report the OLS estimates, while the remaining columns report the IV estimates using the predicted patent stocks as instruments. Firm fixed effects, industry-by-year fixed effects, and ownership type-by-year fixed effects are controlled for in all columns. Columns 3 and 6 further control for the initial median TFP and log value-added output of domestic firms within the county interacted with the year dummies to account for the potential time-varying effects of initial local economic conditions. Standard errors are clustered at the county level in all columns.

Table 3: The Effect of U.S. MNC Innovation on Local Firms' Productivity

Dependent variable		TFP-LP			Labor productivity	
Estimation method	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PatStock^{loc})$	0.106	0.277**	0.297**	0.202**	0.428***	0.438***
	(0.0955)	(0.138)	(0.127)	(0.0997)	(0.157)	(0.146)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Initial conditions X year dummy	No	No	Yes	No	No	Yes
IV test		$F = 20.685$	$F = 20.376$		$F = 20.685$	$F = 20.376$
Observations	221923	221923	221923	221923	221923	221923

Notes: The table presents the regression results of Equation 4. The regression sample includes all local Chinese firms with domestic ownership. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{loc}$ represents the county-level aggregated patent stocks of U.S. multinational firms. Columns 1 and 4 present the OLS estimates, and Columns 2, 3, 5, and 6 show the IV estimates. Each column controls for firm fixed effects, 4-digit Chinese industry-year fixed effects, and ownership type-year fixed effects. Columns 3 and 5 further control for initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Columns 1 and 4 demonstrate that a 10% increase in the patent stocks of U.S. multinational firms with subsidiaries in the local area is associated with a 1.06% increase in domestic firms' TFP and a 2.02% increase in domestic firms' labor productivity, although the former is statistically insignificant. The IV specification in Columns 2 and 5 shows that a 10% increase

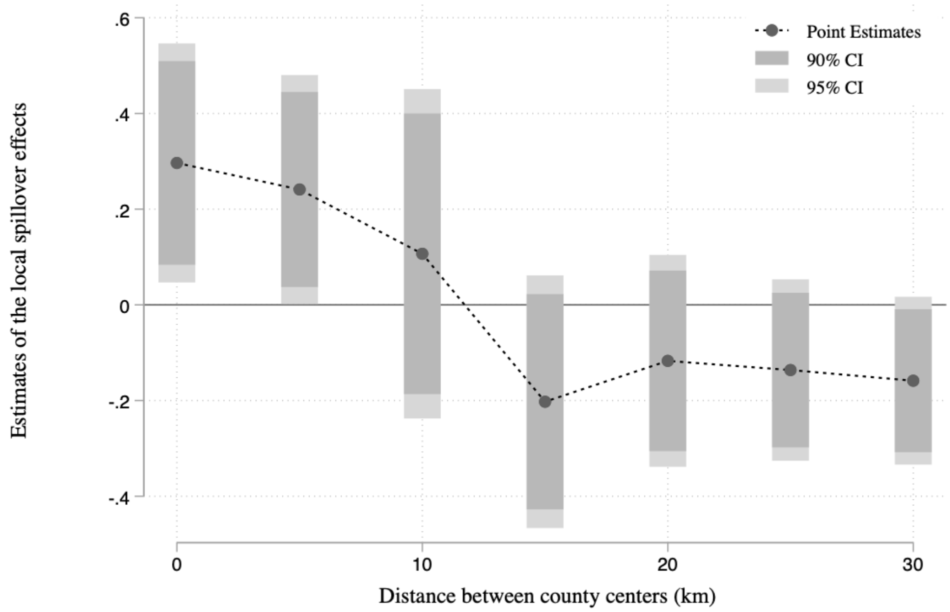
[28] As a validation check, I examine whether the innovation by U.S. multinational firms leads to improvements in productivity by their own subsidiaries in China. As shown in Table A2, both the TFP and labor productivity of the U.S. subsidiaries respond positively to innovation in the parent firm, and the magnitudes of these changes are quantitatively larger than those of the local spillover effects estimated in this section.

in the local patent stocks of U.S. multinational firms improves the domestic firms' TFP by 2.77% and their labor productivity by 4.28%, both of which are statistically significant at at least the 5% level. The estimates remain essentially unchanged when controlling for the interactions between initial county-level economic conditions and year dummies, again suggesting that the estimated effects are not driven by geographic sorting patterns of U.S. multinational subsidiaries. It is notable that the IV estimates are more than twice as large as the OLS estimates, potentially due to either an attenuation bias or the reverse causality issues discussed in section 3.1.

The implied economic magnitude of the estimated local spillover effect in Table 3 is substantial. A one-within-standard-deviation increase (Mummolo and Peterson, 2018) in the local patent stocks of U.S. multinational firms (0.156) leads to a 4.63% rise in the TFP of local domestic firms and a 6.83% rise in their labor productivity. I also compute the economic magnitude of the local spillover effect through a simple back-of-the-envelope calculation: as the median value-added output per worker in a domestic firm is about US $6,100, a 6.83% increase in labor productivity is equivalent to US $416.63 in additional output created by each worker in a median domestic firm.

Numerous past studies establish that technology spillovers are highly geographically localized (Henderson et al., 1993, among others). While the main analysis of this paper focuses on domestic firms located in the same Chinese county as U.S. multinational subsidiaries, I further explore how the strength of the local spillover effect changes with geographic distance. In particular, I examine how the impact of innovation by multinational firms on domestic firms' TFP varies with the distance between the multinational subsidiaries and the domestic firms. As shown in Figure 3, the effect of innovation by multinational firms on domestic firms' TFP decreases rapidly as geographic distance increases. The estimated coefficients are statistically significant at the 5% level for firms within 5 kilometers of U.S. subsidiaries and remain positive within 10 kilometers, and become insignificantly negative at larger geographic distances. These results suggest that the benefits of multinational innovation are highly localized: only domestic firms that are in close geographic proximity to multinational

Figure 3: Distance and Magnitudes of Estimated Effects



Notes: The figure shows how the magnitudes of local technology spillover effects change with geographic distance. I define the distance between a multinational subsidiary and a domestic firm as the geographic distance between the geometric centers of the subsidiary's and the domestic firm's counties in China. For each distance range x, I limit the regression sample of domestic firms to those within x of a U.S. multinational subsidiary and replicate the regression of Column 5, Table 3. Standard errors are clustered at the county level.

subsidiaries garner productivity gains resulting from innovation by multinational firms.[29]

4.2. Robustness checks

I conduct a set of robustness checks to address the following three concerns arising from the findings in Table 3: (i) whether the estimated effect is primarily driven by the entry and exit of local firms; (ii) whether the effect is driven by outsourcing and technology transfers of U.S. multinational firms; and (iii) whether the effect primarily captures a spurious correlation between the economic boom in China and the acceleration of patenting in the U.S. during the early 2000s. I test (i) by restricting the regression sample to local domestic firms established prior to 2000.[30] To address (ii), I restrict the sample to local domestic firms

[29]Interestingly, the effect becomes negative (although largely insignificant) when the distance between two counties is greater than 15 kilometers, suggesting a weak "brain drain" effect of multinational innovation; e.g., the presence of innovative multinational subsidiaries may pull talent away from neighboring areas.

[30]Firm exit is difficult to measure because the ASIE sample is truncated by firm size.

whose export-to-sales ratios are below 50%, as these firms are less likely to rely on foreign contracts. Last, I test (iii) by excluding domestic firms in the four most populated and economically developed prefectures (Beijing, Shanghai, Guangzhou, and Shenzhen) from my sample. Since China's economic boom mainly fuels demand in the most developed regions of China, innovation by multinational firms is unlikely to have a significant impact on domestic firms in less-developed regions if demand shocks are the primary factors driving the results. As shown in Table A3, the local spillover effect remains significantly positive in all three subsamples, suggesting that the findings in Table 3 do not result from any of the above concerns.

Another threat to the identification strategy is that the innovation activities of other non-U.S. multinational firms might be positively correlated with the innovation activities of the U.S. multinational firms (and the U.S. R&D tax credit changes). If that is the case, then the estimated effect of U.S. multinational firms' innovation in Table 3 will be biased upward, as the technological spillovers of other non-U.S. multinational firms with subsidiaries in the sample counties are not accounted for in the estimation. Two pieces of evidence, however, suggest that my estimates are unlikely to be biased by unobserved spillovers from other countries' multinational firms. First, as previously discussed, the U.S. R&D tax credit has little impact on the patenting activities of other non-U.S. patent applicants in EPO and JPO. Second, as shown in Table A4, subsidiaries of non-US multinational firms do not exhibit higher productivity growth when exposed to the higher local patent stocks of U.S. multinational firms, so it is unlikely that the impact of innovation by U.S. multinational firms is propagated through non-U.S. multinational subsidiaries.[31]

Last, I look into whether the local spillover effect is mainly driven by fully owned or partially owned U.S. multinational subsidiaries. Studies such as Javorcik and Spatareanu (2008) and Jiang et al. (2018) find that technology transfers are more prevalent between partially foreign-owned subsidiaries (joint ventures) and domestic firms. If the findings in Table 3 are

[31] Contrary to this prediction, non-U.S. subsidiaries (excluding those from Hong Kong, Macao, and Taiwan) display a lower TFP in counties with a higher U.S. patent stock, suggesting that the innovation of U.S. multinational firms might result in a "crowding out" effect on other foreign-owned subsidiaries with similar levels of technology.

primarily due to voluntary technology transfers from multinational firms, the effects should be predominately driven by partially owned subsidiaries. In Table A5, I construct patent stocks of U.S. multinational firms with fully owned and partially owned subsidiaries in each county and estimate their respective spillover effects. I find that the spillover effects are largely driven by fully owned U.S. subsidiaries, suggesting that the effect of innovation by multinational firms on domestic firms' productivity may not be explained by technology transfer agreements between multinationals and domestic firms.

5. Determinants of Local Firms' Absorptive Capacity

The literature on FDI spillovers indicates that spillover intensity is contingent upon local domestic firms' absorptive capacity, or the ability "to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal, 1990). In this section, I first investigate how firm characteristics, including average wage level (as a proxy for human capital), product innovation (as a measure of innovation capacity), and ownership types (state versus private ownership), may affect the magnitude of spillovers from U.S. multinational firms to local domestic firms. I then look into how technological proximity, measured as the similarity between the domestic industries' patent profiles and the innovation by U.S. multinational firms, may facilitate local spillovers.

5.1. Human Capital, Innovation Capacity, and Ownership

Blalock and Gertler (2009) note that firms conducting R&D investment, firms employing highly educated workers, and firms that are far from technological frontiers are more likely to adopt foreign technology. Griffith et al. (2004) have suggested that R&D activities play a multifaceted role in stimulating innovation and enhancing technology diffusion. In the context of the Chinese economy, studies such as Brandt et al. (2017) show that privately owned enterprises outperform state-owned enterprises in general during 2000-2007. In line with these studies, this section investigates the role of domestic firms' human capital, innovation capacity, and ownership type in the channeling of local technology spillovers.

I first investigate whether human capital facilitates local technology spillovers. Human capital can contribute to firms' absorptive capacity in two ways. First, high-skilled employees are more capable of adopting the use of skill-augmenting foreign technology from multinational firms (Setzler and Tintelnot, 2021). Second, higher-skilled workers at multinational firms are more likely to move to domestic firms with abundant human capital stocks (Poole, 2013). As the ASIE data do not include standard indicators of human capital quality (such as educational attainment), I use each firm's average wage level as an indicator of its human capital quality. I define high-wage firms as those with an average wage above the median level in the corresponding two-digit industry group in the initial year. I then estimate the baseline regression, Equation 4, separately for the sub-samples of high-wage and low-wage firms. The regression results are shown in Columns 1 and 2 of Table 4. I find that the estimated effects on domestic firms' productivity are more pronounced for high-wage firms, consistent with absorptive capacity theory. Moreover, the results suggest that the mobility of highly skilled labor (labor pooling) may play an crucial role in the transmission of foreign knowledge.

Table 4: The Heterogeneous Effect of U.S. MNC Innovation

Dependent variable	TFP-LP					
Sample	$wage > median$	$wage \leq median$	$newproduct > 0$	$newproduct = 0$	$Private = 1$	$State = 1$
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PatStock^{loc})$	0.470***	0.119	0.497***	0.123	0.274*	0.208
	(0.157)	(0.161)	(0.172)	(0.135)	(0.160)	(0.183)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Initial conditions X year dummy	Yes	Yes	Yes	Yes	Yes	Yes
IV test	$F = 20.125$	$F = 23.851$	$F = 41.626$	$F = 29.606$	$F = 7.120$	$F = 12.085$
Observations	89537	132065	36219	185242	152850	33595

Notes: The table shows the heterogeneous local spillover effect of U.S. multinational firms' patent stocks on domestic firms' TFP. The regression sample includes all local Chinese firms with domestic ownership. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{loc}$ represents the county-level aggregated patent stocks of U.S. multinational firms. The IV estimates are reported in all columns. All columns control for firm fixed effects, 4-digit Chinese industry-year fixed effects, ownership type-year fixed effects, and initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

I then examine the role of innovation in domestic firms' absorptive capacity. Following Lu et al. (2017), I define innovative firms as firms that record positive sales of new products in any year during the sample period. I then analyze the sub-samples of innovative and non-innovative domestic firms. As shown in Columns 3 and 4 of Table 4, the effects of $TECH^{loc}$ are concentrated in the domestic firms that conduct product innovation in the sample period, consistent with the finding of Griffith et al. (2004) that innovation by domestic firms may facilitate the imitation of foreign technology.

Finally, I examine how domestic firms with different ownership types may respond differently to technology spillovers. SOEs in China are generally less productive and experience slower growth than private enterprises due to severe agency problems (Hsieh and Klenow, 2009; Brandt et al., 2017). The inherent inefficiency of SOEs may also weaken their absorptive capacity. However, SOEs may have better access to multinational technology through specific technology transfer agreements (Jiang et al., 2018). I empirically examine whether different ownership types (privately owned versus state owned) respond differently to innovation by multinational firms.[32] Columns 5 and 6 of Table 4 show that the local spillover effect is statistically significant and quantitatively larger for the sample of privately owned enterprises, suggesting that privately owned enterprises are better able to absorb foreign technologies than SOEs.

5.2. Technological Proximity

The aggregated local patent stocks of U.S. multinational firms result in significant productivity gains for domestic firms, and the effect is not limited to the few industries in which the U.S. multinational subsidiaries operate.[33] To explain the cross-industry impact of local technology spillovers, I hypothesize that the technological proximity between domestic firms and U.S. multinationals facilitate spillovers beyond industry boundaries: domestic firms with technology profiles closely related to innovation conducted by U.S. multinational firms are better able to appropriate the multinational firms' new technologies. Although technological closeness has been recognized as a key determinant of technology spillovers in the literature on innovation (Bloom et al., 2013), its role has been understudied in the context of FDI

[32]Due to SOE reforms carried out during the sample period, I define a firm as an SOE if it remains state-owned from 2000 to 2007.

[33]Table A6 shows that the local spillover effects are primarily across rather than within industries.

spillovers. The following analysis examines the role of technological proximity in shaping domestic firms' capacity to absorb technological spillovers from U.S. multinational firms.

The detailed U.S. and Chinese patent classifications at the IPC subclass level allows me to construct a technological proximity-based measure of U.S. multinational firms' patent stocks, $PatStock^{prox}$, and to examine its impact on the productivity growth of local domestic firms in each industry in addition to the overall patent stock measure. I estimate the local technology spillover effect through technological linkages by regressing the productivity measures of domestic firms on $PatStock^{prox}$. The baseline specification is similar to Equation 4, in which I control for firm fixed effects, industry-year fixed effects, ownership type-year fixed effects, and initial county-level conditions interacted with year dummies. I further combine the technological proximity-based measure with the previously constructed measure $PatStock^{loc}$ to assess the relative magnitude of spillovers through technological linkages. Finally, I examine the within-county variations of the local spillover effect by incorporating county-year fixed effects.

Table 5: The Effect of U.S. MNC Innovation through Technological Linkages

Dependent variable			TFP-LP		
Estimation method	OLS	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)
$ln(PatStock^{prox})$	0.0430***	0.0680***	0.0662***	0.0491**	0.0521**
	(0.0136)	(0.0220)	(0.0218)	(0.0220)	(0.0216)
$ln(PatStock^{loc})$				0.242	
				(0.165)	
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes
County-year fixed effects	No	No	No	No	Yes
Initial conditions X year dummy	No	No	Yes	Yes	No
IV test		$F = 869.585$	$F = 886.679$	$F = 384.441$	$F = 1331.000$
Observations	211028	211028	211028	211028	211028

Notes: The table shows the spillover effect of local multinational firms' patent shocks on local domestic firms' productivity via technological linkages. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{prox}$ represents the county–industry–level patent stocks of U.S. multinational firms, aggregated based on the technological proximity between the technology profiles of U.S. multinational firms and local domestic industries. All columns report the IV estimates. Each column controls for firm fixed effects, 4-digit Chinese industry-year fixed effects, and ownership type-year fixed effects. Columns 3 and 4 further control for initial local economic conditions interacted with time dummies. Column 5 also controls for county-year fixed effects. Robust standard errors are clustered at the county-by-industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 5 provides evidence that technology spillovers through technological linkages, $Patstock^{prox}$, improve domestic firms' TFP and labor productivity in the local areas, in addition to the overall local spillover effects. A one-within-standard-deviation increase (0.571) is associated with a 2.5% increase in local domestic firms' TFP (Column 1) and is linked to a 3.8% TFP improvement (Columns 2 and 3). The effect remains statistically significant after controlling for the aggregated county-level multinational patent stocks. The coefficient for $ln(PatStock^{loc})$ is statistically insignificant, and the economic magnitude of $ln(PatStock^{prox})$ is over 70% of the overall local spillover effect.[34] Last, I find that the technological proximity-based local spillover effect persists after controlling for a county-year fixed effect (Column 5), indicating that the local technological externalities of U.S. multinational subsidiaries are more likely to be captured by local domestic firms with similar technological profiles to the U.S. multinationals than by other domestic firms in the same county. The findings of Table 5 suggest that a substantial proportion of cross-industry local spillovers are facilitated by domestic firms adopting related technological knowledge from the U.S. multinational firms.

6. Concluding Remarks

Using a novel methodological approach involving matching U.S. multinational firms with their manufacturing subsidiaries in China and an identification strategy based on U.S. R&D tax credit policies, this study provides new empirical evidence on the impact of innovation by multinational firms on the productivity growth of domestic firms. I find that innovation by U.S. multinational firms leads to a significant increase in the productivity of domestic firms located near these multinationals' subsidiaries, indicating a local technology spillover effect. I further investigate the role of domestic firms' absorptive capacity in the channeling of local technology spillovers. I find local domestic firms with high-quality human capital, innovation experience, or private ownership realize higher productivity gains when exposed

[34] A one within standard deviation increase of $PatStock^{prox}$ (0.571) leads to a 2.8% increase in domestic firms' TFP when controlling for the overall patent stocks. A one-within-standard-deviation increase of $PatStock^{loc}$ (0.156) improves TFP by around 3.8% (the effect is statistically insignificant). The relative size of the local spillovers through technological linkages is hence approximately 2.8%/3.8%73.7%.

to innovation by multinational firms. Notably, the multinational firms' technological knowledge also carries over to domestic firms through technological linkages. Domestic firms with closer technological ties to the innovation by multinational firms garner greater productivity gains than other domestic firms within the same county.

The paper contributes to the previous literature on FDI spillover in two ways. First, it constructs a patent-based measure of multinational firms' local presence based on matched parent–subsidiary data, extending the scope of the previous studies that primarily focus on the size-based FDI spillover measures. Second, the paper introduces a novel IV strategy based on innovation policies in the home country of multinational firms, which overcomes a number of identification challenges faced in the previous studies.

The findings of this paper suggest several directions for future research. Although the study sheds light on the potential channels for local technology spillover effects, the empirical evidence is largely indirect. The hypotheses about technological learning and labor pooling could be further tested using detailed employee–employer matched data. Second, patent-based measures are often considered an inadequate method by which to accurately measure innovation or technological progress. Alternative measures, such as product innovation or technology adoption, could also be exploited. Finally, the empirical approach in this paper could be applied under other contexts to verify the existence of local technology spillovers resulting from innovation by multinational firms and to expand the generality of this study.

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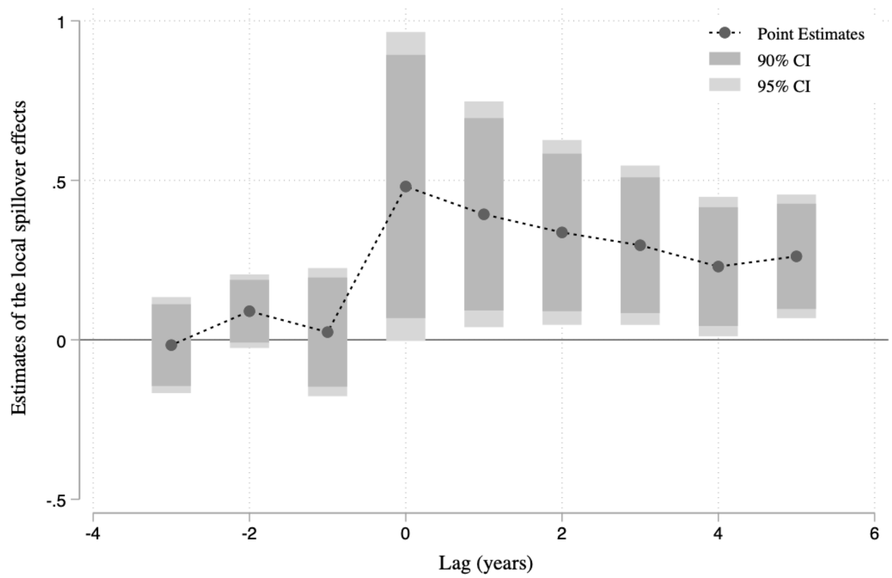
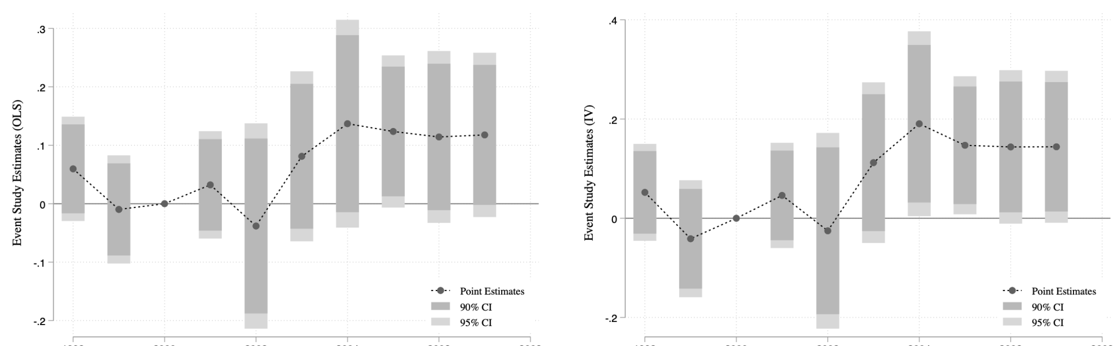
Appendix A Additional Figures and Tables

Figure A1: Lead-Lag Effects



Notes: The figures show the relationship between the estimated effects of U.S. multinational firms' patent stocks on local firms' TFP and lagged years. IV estimates and the corresponding 95% confidence intervals are shown in the figure. Standard errors are clustered at the county level.

Figure A2: Event Study Plots



Notes: Notes: The figure shows the OLS and IV estimates of the event study coefficients. The event study analysis regresses the TFP of local firms on the growth of U.S. multinational firms' patent stocks interacted with year dummies. The regressions control for firm fixed effects, 4-digit Chinese industry-by-year fixed effects, ownership type-by-year fixed effects, and initial local economic conditions interacted with time dummies. The OLS estimates are shown in the left panel, and the IV estimates are shown in the right panel. Standard errors are clustered at the county level.

Table A1: Inclusion Restriction Checks for Technological Proximity-based Measures

Dependent variable	ln(SimpleCounts)		ln(CitationWeightedCounts)	
	(1)	(2)	(3)	(4)
rho^h_{t-3}	-1.978***	-1.616***	-3.502***	-3.076***
	(0.351)	(0.415)	(0.606)	(0.750)
Firm-state-IPC fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Firm-specific year trends	No	Yes	No	Yes
State-specific year trends	No	Yes	No	Yes
IPC-specific year trends	No	Yes	No	Yes
Observations	4333910	4333910	4333910	4333910

Notes: The table presents the inclusion restriction checks for the instrumental variable of the technological proximity-based patent stock measures. The regressions are conducted at the U.S. firm–state–IPC subclass level, with robust standard errors clustered at the state–year level. The dependent variable of Columns 1 and 2 is the natural log of simple counts of patent applications, and the dependent variable of Columns 3 and 4 is the natural log of citation weighted counts of patent applications. Each column controls for firm–state–IPC fixed effects and year fixed effects. Columns 2 and 4 further control for firm-specific, state-specific, and IPC-specific year trends. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A2: The Effect of U.S. MNC Innovation on Subsidiaries' Productivity

Dependent variable	TFP-LP			Labor productivity		
Estimation method	OLS	IV	IV	OLS	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PatStock^{mnc})$	0.621**	0.637**	0.621**	0.480**	0.583*	0.571**
	(0.244)	(0.285)	(0.261)	(0.204)	(0.311)	(0.283)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Median size and TFP of domestic firms	No	No	Yes	No	No	Yes
IV test		$F = 40.274$	$F = 40.752$		$F = 40.274$	$F = 40.752$
Observations	1988	1988	1988	1988	1988	1988

Notes: The table presents the estimates of the effect of U.S. multinational firms' patent stocks on the productivity of their subsidiaries in China. Regressions are weighted using the adjusted initial employment of the firms. $PatkStock^{mnc}$ represents the 3-year lagged multinational parents' patent stocks in the U.S. Columns 1 and 4 show the OLS estimates, and Columns 2, 3, 5, and 6 present the instrumental variable (IV) estimates. Each column controls for firm fixed effects, 4-digit Chinese industry by year fixed effects, and ownership type-by-year fixed effects. Columns 3 and 6 further control for the average log of the value-added output and the average TFP of local domestic firms. Robust standard errors are clustered at the parent firm level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Robustness Checks

Dependent variable	TFP-LP	Labor prod.	TFP-LP	Labor prod.	TFP-LP	Labor prod.
Sample	begin year $\leq$ 2000		export share $<$ 0.5		major cities excluded	
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PatStock^{loc})$	0.320**	0.468***	0.269*	0.463***	0.185*	0.340**
	(0.130)	(0.149)	(0.142)	(0.159)	(0.106)	(0.142)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Initial conditions X year dummy	Yes	Yes	Yes	Yes	Yes	Yes
IV test	$F = 20.577$	$F = 20.577$	$F = 22.229$	$F = 22.229$	$F = 17.647$	$F = 17.647$
Observations	167902	167902	187223	187223	136211	136211

Notes: The table presents the regression results of three sets of robustness checks. Regressions are weighted using the adjusted initial employment of the firms. $PatStock^{loc}$ represents the 3-year lagged county-level aggregated patent stocks of U.S. multinational firms. IV estimates are shown in all columns. Each column controls for firm fixed effects, 4-digit Chinese industry-by-year fixed effects, ownership type-by-year fixed effects, and initial local economic conditions interacted with time dummies. Columns 1 and 2 restrict the sample to local domestic firms established before 2000. Columns 3 and 4 restrict the sample to local domestic firms with export shares less than 50%. Columns 5 and 6 exclude local domestic firms in the most developed regions: Beijing, Shanghai, Guangzhou, and Shenzhen. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A4: The Effect of U.S. MNC Innovation on Non-U.S. Subsidiaries' Productivity

Dependent variable	TFP-LP	Labor prod.	TFP-LP	Labor prod.	TFP-LP	Labor prod.
Sample	foreign ownership $>$ 0		Hong Kong, Macao, and Taiwan		Other sources	
	(1)	(2)	(3)	(4)	(5)	(6)
$ln(PatStock^{loc})$	-0.00475	-0.0438	0.0435	-0.0520	-0.178**	-0.127
	(0.101)	(0.109)	(0.106)	(0.136)	(0.0771)	(0.0798)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Initial conditions X year dummy	Yes	Yes	Yes	Yes	Yes	Yes
IV test	$F = 32.756$	$F = 32.756$	$F = 31.986$	$F = 31.986$	$F = 45.316$	$F = 45.316$
Observations	143887	143887	84218	84218	59260	59260

Notes: This table presents the estimated effect of U.S. multinational firms' patent stocks on the productivity of non-U.S. subsidiaries. Columns 1 and 2 include all local firms with foreign ownership. Columns 3 and 4 include local firms with major ownership from Hong Kong, Macao, and Taiwan, and Columns 5 and 6 include local firms with major ownership from other foreign sources. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{loc}$ represents the 3-year lagged county-level aggregated patent stocks of U.S. multinational firms. IV estimates are shown in all columns. Each column controls for firm fixed effects, 4-digit Chinese industry-by-year fixed effects, ownership type-by-year fixed effects, and initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A5: The Effects of Fully and Partially Owned Subsidiaries

Dependent variable	TFP-LP		Labor productivity	
Estimation method	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
$ln(PatStock^{loc,full})$	0.220**	0.554*	0.199**	0.383
	(0.0860)	(0.308)	(0.0945)	(0.303)
$ln(PatStock^{loc,partial})$	-0.0334	-0.0351	0.0720	0.0454
	(0.0471)	(0.146)	(0.0593)	(0.196)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes
Initial conditions X year dummy	Yes	Yes	Yes	Yes
IV test		$F = 3.450$		$F = 3.450$
Observations	221923	221923	221923	221923

Notes: The table shows the local spillover effects of fully owned U.S. multinational subsidiaries and partially owned U.S. multinational subsidiaries. $PatStock^{loc,full}$ represents the 3-year lagged county-level aggregated patent stocks of the U.S. multinational firms that have fully owned subsidiaries in the county. $PatStock^{loc,partial}$ represents the county-level aggregated patent stocks of the U.S. multinational firms that have partially owned subsidiaries in the county. IV estimates are shown in all columns. Each column controls for firm fixed effects, 4-digit Chinese industry-by-year fixed effects, ownership type-by-year fixed effects, and initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table A6: The Effect of U.S. MNC Innovation Within and Across Industries

Dependent variable	TFP-LP (1)	Labor prod. (2)	TFP-LP (3)	Labor prod. (4)	TFP-LP (5)	Labor prod. (6)
$ln(PatStock^{within})$	0.0496 (0.0896)	0.0809 (0.104)				
$ln(PatStock^{upstream})$			0.135*** (0.0423)	0.157*** (0.0439)		
$ln(PatStock^{downstream})$					0.0885*** (0.0316)	0.117*** (0.0395)
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Initial conditions X year dummy	Yes	Yes	Yes	Yes	Yes	Yes
IV test	$F = 61.593$	$F = 61.593$	$F = 55.584$	$F = 55.584$	$F = 54.815$	$F = 54.815$
Observations	27627	27627	221768	221768	221768	221768

Notes: The table presents the regression results for the within-industry and cross-industry local spillover effects of U.S. multinational firms' patent stocks. Columns 1 and 2 report the estimated within-industry effect, Columns 3 and 4 report the estimated cross-industry effect of upstream U.S. multinational firms' patent stocks, and Columns 5 and 6 report the estimated cross-industry effect of downstream U.S. multinational firms' patent stocks. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{within}$ represents the county-level aggregated patent stocks of U.S. multinational firms in the same industries as the domestic firms. $PatStock^{upstream}$ represents the county-level aggregated patent stocks of U.S. multinational firms in the upstream industries of the domestic firms; $PatStock^{downstream}$ represents the county-level aggregated patent stocks of U.S. multinational firms in the downstream industries of the domestic firms. All columns report the IV estimates. All columns control for firm fixed effects, IO sector-year fixed effects, ownership type-year fixed effects, and initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county and IO sector levels. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Appendix B Matching Procedure and Outcomes

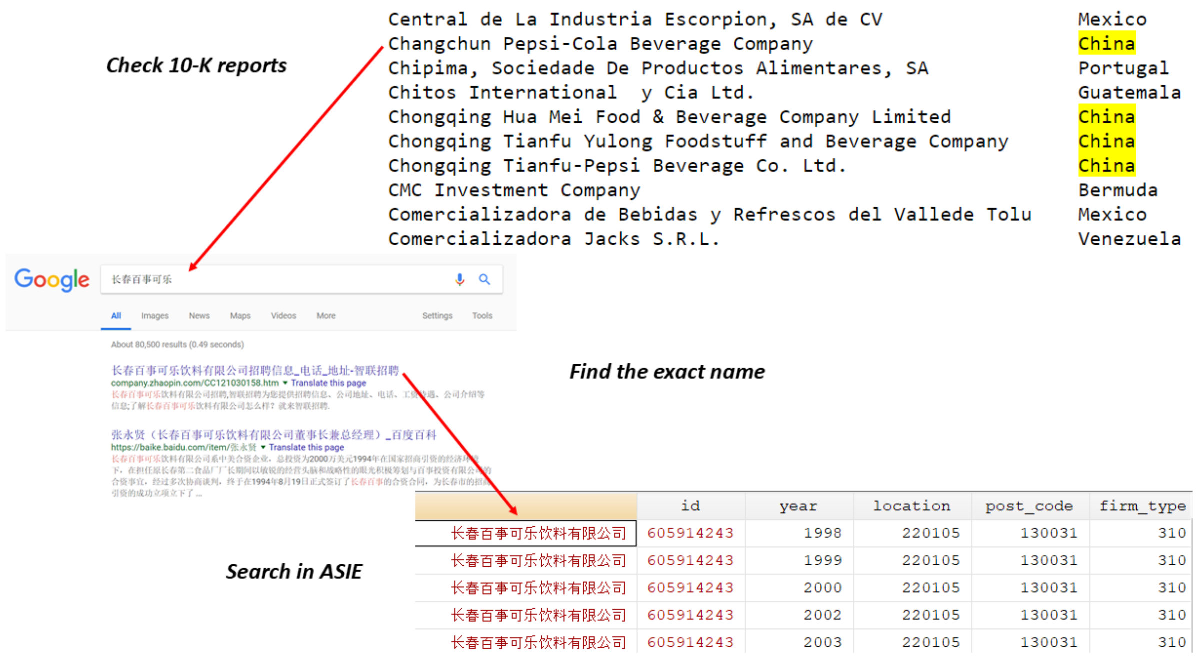
The matching procedure can be divided into the following steps:

1. **Textual scraping**: I download all 10-K files for U.S. public firms from SEC Edgar and search for the keywords indicating that a firm potentially has business connections with China. The keywords are combinations of two sets of words within one sentence: first, any word in the list "subsidiary(ies), operation, facility(ies),investment, venture"; and second, either "China" or "Chinese."
2. **Manual matching**: Based on the information in the 10-K files for the selected firms, I manually match the firm names to the ASIE data after translating the names into Chinese. The main data source used is the Exhibit 21 table, which lists all subsidiaries' names and countries (if outside the U.S.). I also search for and include the names in the main text (if any).
3. **Supplementing with Orbis**: I supplement the 10-K-based matches with the parent–subsidiary information in Orbis.[35] The subsidiary names in the Orbis data are then matched to the ASIE data using the same name matching procedure.
4. **Sample cleaning**: I match the parent company information to the Compustat data and to the USPTO patent data. I restrict the sample to U.S.-based parent companies that exist between 2000 to 2007 in the Compustat data and the subsidiaries that appear before 2000 in the ASIE data. The parent companies are also included in the crosswalk in Autor et al. (2020).

I use Pepsi Co. an example to illustrate the matching procedure in Figure B1. After identifying Pepsi as a multinational firm that operates in China, I examine the Exhibit 21 Tables in its 1998, 1999, and 2000's 10-K files. The table shows that Pepsi have four subsidiaries in China before 2000, one located in Changchun and three located in Chongqing. For each of the subsidiary names, I search for the combination of the city name and Pepsi in Chinese in the search engine to identify the official Chinese name of the subsidiary. I then search for the Chinese name in the ASIE data, which then provides the firm identifier and the business information of the subsidiary between 2000 and 2007.

[35] The Orbis data contain subsidiaries of large U.S. multinational firms in more recent years

Figure B1: Example of Name Matching Procedure



Note: This figure shows an example of Pepsi Co. of the matching procedure.

Table B1: Matching Outcomes by Step

	U.S. Firms	Subsidiaries	Total employment
Number of Public Firms	4918		
Mentioning China	1148		
Identified subsidiaries from 10-K	224	410	164,206
Add ORBIS subsidiaries	235	452	186,401
Match to patent data	171	334	132,424

Notes: The table lists the number of U.S. firms, their Chinese subsidiaries, and the total initial employment of the matched subsidiaries as reported in the ASIE data.

Table B1 shows the matching outcomes for each step of the matching procedure. I eventually match 171 U.S. public firms with 334 Chinese subsidiaries. The total employment of those subsidiaries in the year 2000 is 132,424.

Table B2 presents the 15 largest U.S. multinational firms in China in 2000. In 2000, the largest multinational by employment in my sample is Motorola Solutions Inc., which employed over 13,000 people in total and reported sales of over 34 billion yuan (over US $4 billion). Notably, most of the matched multinational firms are in high-tech industries, such as the electronics industry (Motorola, Flextronics, Emerson), the machinery industry (United

Table B2: Top 15 U.S. MNCs in China by Total Initial Employment

Company names	# subsidiaries	Employment	Sales (million yuan)
MOTOROLA SOLUTIONS INC	2	13514	34210
FLEXTRONICS INTERNATIONAL	5	10173	6080
EMERSON ELECTRIC CO	10	8935	2630
UNITED TECHNOLOGIES CORP	5	8199	7687
PULSE ELECTRONICS CORP	1	6500	631
GENERAL ELECTRIC CO	9	6246	2382
PEPSICO INC	14	5816	3578
SOLECTRON CORP	3	4935	5344
NIKE INC	1	4108	375
MATTEL INC	1	3695	109
ITT INC	7	3518	449
CUMMINS INC	5	2821	1076
DEERE & CO	2	2814	216
CTS CORP	1	2667	1262
PROCTER & GAMBLE CO	3	2217	4256

Notes: The table presents the top 15 U.S. multinational firms (ranked by their total initial employment) operating in China, their number of subsidiaries, their total initial employment, and their total initial sales.

Technologies, General Electric, Cummins), and the chemical industry (DuPont and Procter & Gamble).

Appendix C Variable Construction and Definition

The key variables used in my analysis are constructed and defined as follows:

1. Value-added: The main output measure used in the analysis. In the ASIE data, it is computed using the formula

   $$\textit{Value-added} = \textit{Gross output} - \textit{Intermediate input} + \textit{Value-added tax}$$

   Another commonly used definition of value-added is

   $$\textit{Value-added} = \textit{Fixed asset depreciation} + \textit{Wagebill} + \textit{Net taxes} + \textit{Operating surplus}$$

   For computational convenience, I replace the non-positive values using the minimum positive value within each 2-digit industry–year group.

2. Gross output: Gross output is directly reported in the ASIE data.
3. Employment: The number of employees is directly reported in the ASIE data. I replace 0 values with 1.
4. Capital: Following Brandt et al. (2017), I use the perpetual inventory method to construct real capital measures. I replace the non-positive values using the minimum positive value within each 2-digit industry–year group.
5. Wagebill: Wagebill is directly reported in the ASIE data. For consistency with the other variable constructions, I replace wagebill with value-added if wagebill is larger than value-added.
6. Wage: Average wage is computed by wagebill/employment.

Appendix D TFP Estimation

I assume the following Cobb–Douglas value-added production function:

$$y_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \omega_{it} + \epsilon_{it}$$

where y_{it} is gross output, k_{it} is capital, l_{it} is labor input, m_{it} is intermediate input, $\omega_i t$ is the persistent productivity term, and ϵ_{it} represents the transitory productivity shocks. I estimate the production function separately for each 2-digit Chinese industry.

Following Levinsohn and Petrin (2003), I assume that firms' intermediate input demand is a function of capital input and the unobserved productivity term, ω_{it}:

$$m_{it} = \tilde{m}(k_{it}, \omega_{it}).$$

I then write the unobserved productivity term ω_{it} as a function of capital and intermediate inputs: $\omega_{it} = \tilde{\omega}(k_{it}, m_{it})$. Substituting the expression into the production function gives the following:

$$y_{it} = \beta_0 \beta_l l_{it} + \beta_k k_{it} + \tilde{\omega}(k_{it}, m_{it}) + \epsilon_{it} = \beta_l l_{it} + \Phi(k_{it}, m_{it}) + \epsilon_{it},$$

where $\Phi(k_{it}, m_{it}) = \beta_0 + \beta_k k_{it} + \beta_m m_{it} + \tilde{\omega}(k_{it}, m_{it})$.

In the first step of the estimation, I assume that $\Phi(k_{it}, m_{it})$ can be approximated by a fourth-degree polynomial of k_{it} and m_{it} to estimate β_l and $\Phi(k_{it}, m_{it})$. Following Brandt et al. (2017), I also control for ownership, year, province, and 4-digit industry fixed effects. In the second step, I assume that the law of motion of ω can be written as

$$\omega_{it} = g(\omega_{it-1}) + \xi_{it}$$

where $g(\omega_{it-1})$ is a third-order polynomial function of ω_{it-1}. I estimate β_k and β_m using a generalized method of moments (GMM) method with the following moment condition:

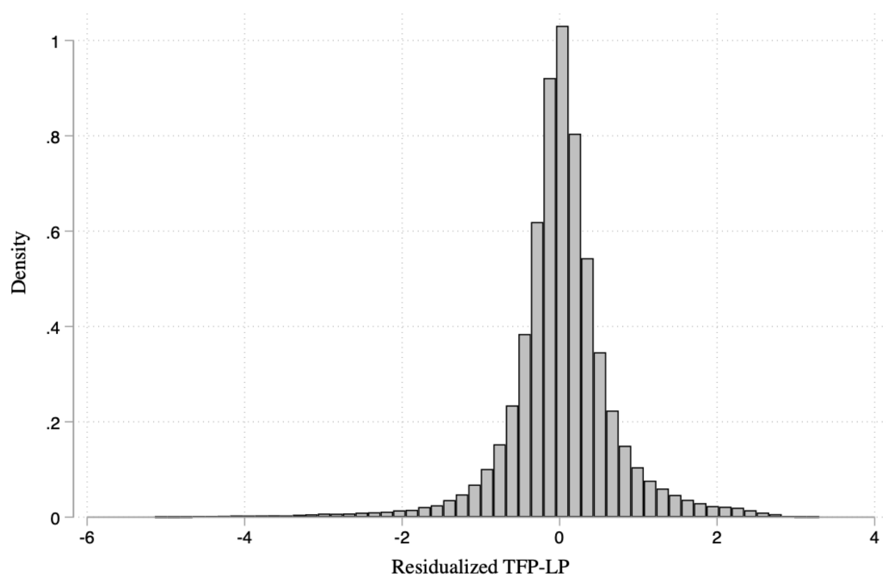
$$\mathbb{E}\left(\xi_{it} \begin{pmatrix} k_{it} \\ k_{it-1} \\ m_{it-1} \\ m_{it-2} \\ l_{it-1} \end{pmatrix} \right) = 0$$

Last, I estimate each firm's TFP as the residual term of the production function:

$$\hat{\omega}_{it} = y_{it} - \hat{\beta}_0 - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it} - \hat{\beta}_m m_{it}$$

I present the distribution of the residualized estimated TFP-LP in Figure D1 after excluding firm fixed effects, industry–year fixed effects, and ownership type–year fixed effects. The distribution is fairly normal, although with a long left tail.

Figure D1: Distribution of Residualized TFP-LP



Notes: The figure shows the sample distribution of the residualized estimated TFP after excluding firm fixed effects, industry–year fixed effects, and ownership–year fixed effects. The top and bottom 1% are trimmed to exclude outliers.

Appendix E Discussion of the Instrument

E.1 Instrumental Variable Construction

R&D tax credits play a key role in the U.S. economy and in corporate innovation activities. In 2015, the total R&D expenditure in the U.S. was about $495 billion. About 70%, or $355 billion, of this total came from the private sector. Total R&D expenditure accounts for about 2.7% of the U.S.'s total GDP, with the private sector R&D accounting for about 1.9%[36]. Government support for business R&D expenditures accounted for 0.25% of total GDP in the U.S. in 2015, and approximately 30% of the funding (0.07% of GDP) was in the form of tax incentives[37]. This volume of government support therefore accounts for about 13% of total business R&D expenditures in the U.S., while the tax incentives account for about 4%.

The most common type of R&D tax credit is a tax credit applied to incremental R&D expenditures, or R&D expenditures above some base level. Here I take California as an example. Since 2000, California has provided an R&D tax credit of 15% for qualified research expenses (QRE). The amount of R&D tax credit is computed through the following steps[38]:

1. Step 1: Identify the current-year qualified R&D expenses.
2. Step 2: Calculate the base-period percentage. The base percentage is defined as the percentage of qualified research expenses in gross receipts for at least three years during the period from 1984 to 1988, capped at 16%.
3. Step 3: Calculate the R&D base amount. The R&D base amount is computed as the average annual gross receipts from the last three years multiplied by the base-period percentage.
4. Step 4: Calculate the R&D tax credit. This is computed by dividing the excess amount of the current-year qualified R&D expenses by the base amount multiplied by the tax credit rate (15%).

[36] See Fact Sheet–Research & Development by the Numbers, R&D Coalition.
[37] See Measuring Tax Support for R&D and Innovation, OECD.
[38] A detailed illustration and examples are provided in An Overview of California's Research and Development Tax Credit.

Table E1: Illustrative Example of R&D Tax Credit Calculation

An example of R&D tax credit calculation (Microsoft, 2015)	
Step 1: Identify current-Year qualified R&D expenses	
R&D expenses	12046
Step 2: Calculate base-period percentage	
1984-1988 gross receipts	1275
1984-1988 RDC expenses	145
R&D expenses as a percent of gross receipts	11.40%
Step 3: Calculate R&D base amount	
Average annual gross receipts for 2011-2014	79341
Apply base-period percentage	11.40%
Base amount	9055
Step 4: Calculate tax credit	
Excess QRE	2991
Apply tax credit rate	15%
Tax credit amount	**449**

Notes: The table shows an example of how R&D tax credit is calculated. I apply the R&D tax credit rate in California in 2015 to Microsoft, assuming all its R&D expenditures are incurred in California.

I provide a simple numerical example in Table E1. I use Microsoft as an example and assume that all of its R&D expenditures are incurred in California. The calculated tax credit amount is about 3.7% of total R&D expenditure in 2015.

Following previous studies, I use the user cost of R&D capital to instrument for the U.S. firms' innovation activities. Intuitively, the user cost of R&D capital is the opportunity cost of R&D investment, or the implicit rental rate of R&D capital after tax. As in Wilson (2009), the user cost of R&D capital is derived using the Hall–Jorgenson formula (Hall and Jorgenson (1967)):

$$\rho_{it} = \frac{1 - s(k^e_{it} + k^e_{ft}) - z_t(\tau^e_{it} + \tau^e_{ft})}{1 - (\tau^e_{it} + \tau^e_{ft})}[r_t + \delta]$$

where i denotes state-level variables, f denotes federal-level variables, r_t is the real interest rate, δ is the economic depreciation rate of R&D capital, τs are effective corporate tax rates, z_t is the present discounted value of the tax depreciation allowance, and s is the share of R&D expenditures that qualifies for special tax treatment.

E.2 Identification Assumptions

The exclusion restriction assumption requires that the instrumental variable is not uncorrelated with the error terms in the second stage regression; that is, $Cov(\widehat{PatStock}^{loc}_{ct-3}, \epsilon_{it}|X_{it}) =$

0. In this section, I discuss how the instrumental variable strategy may fulfill the identification assumption and address the two types of endogeneity problems with OLS: omitted variable bias and reverse causality.

Table E2: U.S. R&D Subsidy and Patenting in EU and Japan, IPC Subclass Level

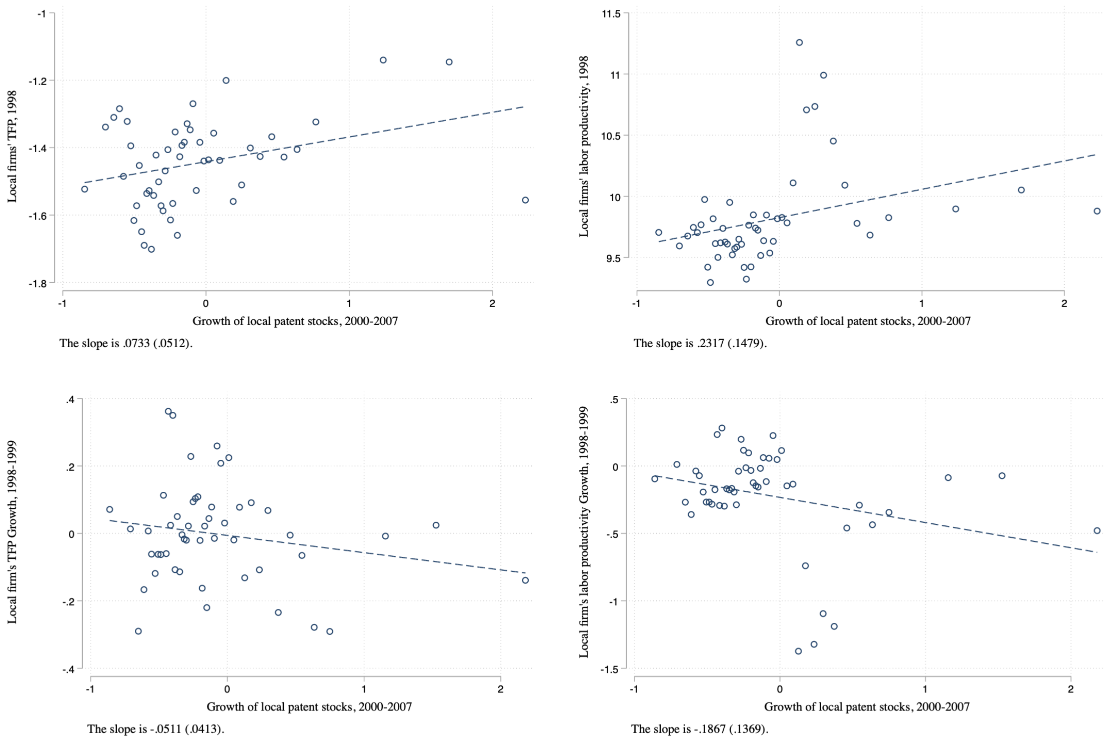
Dependent variable	$ln(PatCounts_{EPO}^{Non-US})$ (1)	$ln(PatCounts_{EPO}^{US})$ (2)	$ln(PatCounts_{JPO}^{Non-US})$ (3)	$ln(PatCounts_{JPO}^{US})$ (4)
$(\overline{rho_{t-3}^h})_{ipc}$	-0.779	-9.144***	-0.381	-1.173
	(2.635)	(2.916)	(2.407)	(0.815)
IPC fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Observations	13335	13335	13335	13335

Notes: the table shows the effect of U.S. R&D tax credit policies on patenting in EPO and JPO at the IPC subclass level. $(\overline{rho_{t-3}^h})_{ipc}$ is the weighted average of R&D tax credit-induced R&D capital user cost, using U.S. firms' patenting in each state within the IPC subclass during 1975-2010 as weights. $PatCounts_{EPO/JPO}^{US/Non-US}$ is the patent applications of U.S. (non-U.S.) applicants in EPO (JPO) in the IPC subclass. Robust standard errors are clustered at the IPC subclass level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

The omitted variable bias problem may threaten our identification method when the R&D tax credit policy in the U.S. is correlated with other unobserved shocks to the local domestic firms in China. In one possible scenario, the US R&D tax credit policy may affect not only U.S. multinational firms, but also multinational firms from other developed countries operating in China. As a result, the estimate of the local spillover effect in Table 3 will be biased upward because the productivity growth of local firms is affected by both the U.S. multinational innovation shocks and the unobserved non-U.S. multinational innovation shocks. Using patent application data from Patstat from 1975 to 2010, I rule out this possibility by examining how patenting activities outside the USPTO—specifically, patenting under the European Patent Office (EPO) and the Japan Patent Office (JPO)—are affected by the R&D tax credit-induced changes in R&D capital user cost. I aggregate the number of patent applications at the IPC subclass level and compute the corresponding weighted average U.S. R&D capital user cost at the IPC subclass level, using the shares of patent applications within the IPC subclass in each U.S. state as weights. I further sort the patent applications in EPO and JPO based on whether the applicants come from the U.S. As shown in Table E2, patent applications by non-U.S. applicants to both the EPO and JPO are not affected by the 3-year lagged U.S. R&D capital user cost, while patent applications by U.S.

applicants in the EPO are significantly reduced by the R&D capital user cost. These results suggest that U.S. R&D tax credit policies are unlikely to affect innovation of firms outside the U.S.[39]

Figure E1: Ex-ante Economic Outcomes and Ex-post Patent Stock Changes

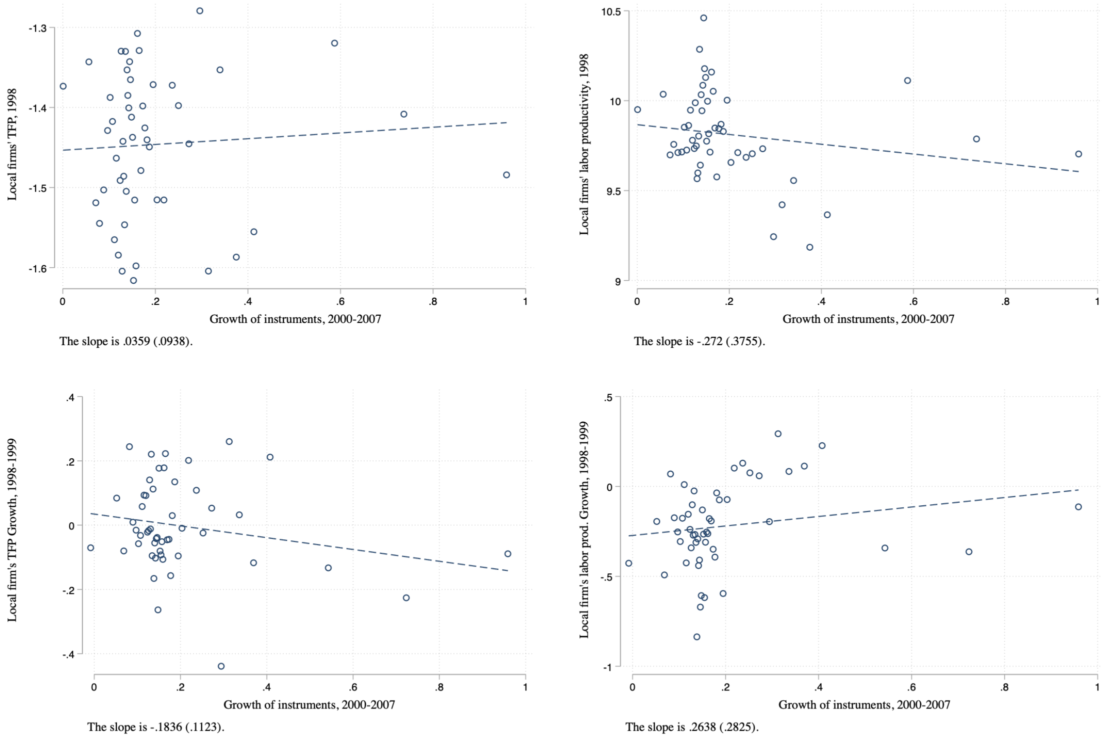


Notes: The figures show the relationship between the ex-ante economic outcomes and the ex-post changes in U.S. multinational firms' local patent stocks. Each figure presents a binscatter plot (and a linear fit) that represents the correlation between an ex-ante outcome variable for local firms and the ex-post changes in the local patent stocks after controlling for industry fixed effects. The first row of figures shows the correlation between the levels of local firms' TFP and and labor productivity in 1998 and the changes to the local patent stocks between 2000 and 2007. The second row of figures shows the correlation between the changes in local firms' TFP and labor productivity from 1998 to 2000 and the changes in the local patent stocks between 2000 and 2007.

Another possible source of omitted variable bias is sorting, which arises when multinational firms with different innovation capacities sort into Chinese counties with different characteristics. I conduct a set of placebo tests that regress local firms' *ex-ante* outcomes on the *ex-post* instrumental variable changes. I use the levels and growth of domestic firms' TFP and labor productivity from 1998 to 2000 as the *ex-ante* firm outcomes and test their corre-

[39]Table A4 also shows that the local patent stocks of U.S. multinational firms have trivial or even adverse effects on non-U.S. multinational subsidiaries.

Figure E2: Ex-ante Economic Outcomes and Ex-Post Instrument Changes

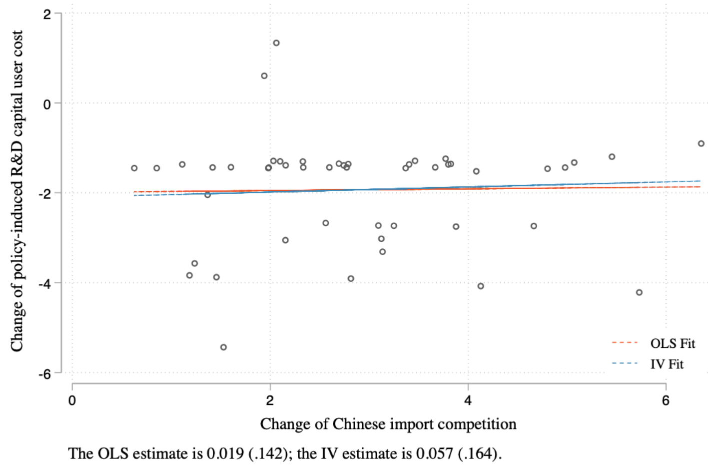


Notes: The figures show the relationship between the ex-ante economic outcomes and the ex-post changes in U.S. multinational firms' predicted local patent stocks (the IV). Each figure presents a binscatter plot (and a linear fit) that represents the correlation between an ex-ante outcome variable for local firms and the ex-post change in the predicted local patent stocks after controlling for an industry fixed effects. The first row of figures shows the correlation between the levels of local firms' TFP and labor productivity in 1998 and the changes in the predicted local patent stocks between 2000 and 2007. The second row of figures shows the correlation between the changes in local firms' TFP and labor productivity from 1998 to 2000 and the changes in the predicted local patent stocks between 2000 and 2007.

lations with the change in the county-level user cost of R&D capital from 2000 to 2007 (and the change in the county-level U.S. patent stocks from 2000 to 2007). The test results are presented in Figure E2. The results imply that there are only weak correlations between the changes in the local firms' outcomes before 2000 and the changes in the corresponding user cost of R&D capital after 2000. Furthermore, the correlations between the *ex-ante* changes in the local firms' outcomes and the patent stock growth after 2000 are also insignificant, as shown in Figure E1, implying that sorting is unlikely to introduce significant bias in the OLS and IV estimates.

The reverse causality problem may occur if the U.S. R&D tax credit policy is affected by

Figure E3: Chinese Import Competition and R&D Tax Credits



Notes: The figure shows the scatter plot of the state R&D tax credit-induced changes in the user cost of R&D capital from 2000 to 2007 versus state-level import competition changes from 2000 to 2007 based on Autor et al. (2013). Using import competition with other high-income countries as the instrument, the dotted red line represents the OLS fit, and the dotted blue line represents the IV fit.

any local shocks from China. The R&D tax credit was introduced in the Economic Recovery Tax Act of 1981, far before China joined the WTO (and the starting year of our sample period), so it is unlikely that the initiation of R&D tax credit programs is caused by any local shocks from China. State-specific R&D tax credits, on the other hand, are introduced and modified separately by each state, and these state-level policy changes may be affected by, for instance, growth in the Chinese economy. A comparison of changes in state-level R&D tax credits and changes in Chinese import competition between 2000 and 2007 (Autor et al., 2013) provides some evidence that such a reverse causality problem is unlikely. As shown in Figure E3, the changes in state-level R&D tax credits are not correlated with any Chinese import competition shocks in the U.S. or in other high-income countries, suggesting that the instrumental variable, e.g., the U.S. state-level R&D tax credit policies, is unlikely to be directly affected by economic shocks in China.

My identification strategy relies on a local-level R&D subsidy-based instrument that could be categorized as a "shift-share" instrumental variable (SSIV) as in Bartik (1991) and Autor et al. (2013). Recent studies such as Adao et al. (2019), Borusyak et al. (2022), and Goldsmith-Pinkham et al. (2020) point out that the validity of the SSIV strategy relies on several additional assumptions, and the conventional shift-share (Bartik) methods may underestimate the standard errors of the estimators.

Table E3: Shock Level regressions

Dependent variable	$\overline{\Sigma PatStock}$	$\overline{TFP-LP}$	$\overline{TFP-LP}$
Model	1st Stage	OLS	IV
	(1)	(2)	(3)
$\overline{\Sigma \widehat{PatStock}}$	2.289***		
	(0.739)		
$\overline{\Sigma PatStock}$		0.0721	0.344**
		(0.0783)	(0.151)
US MNC fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	1368	1368	1368

Notes: The table presents equivalent shock-level (U.S. multinational-level) regressions for Column 5, Table 3, following Borusyak et al. (2022). I convert the local-level IV, patent stocks, and TFP to the corresponding exposure-weighted, shock-level aggregates. Industry-year and ownership-year fixed effects are absorbed in the conversion. U.S. multinational fixed effects and year fixed effects are controlled for in all columns. Robust standard errors are clustered at the U.S. multinational level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

I follow Borusyak et al. (2022) in demonstrating the validity of my instrumental variable strategy. One can imagine an idealized experiment in which the U.S. policy instruments are randomly assigned to the Chinese counties (through multinational operations). It is arguably true that the policy instruments are orthogonal to the unobserved local shocks in the Chinese counties, satisfying Assumption One in Borusyak et al. (2022). Assumption Two requires the policy shocks to be uncorrelated across multinational firms and for exposure to each multinational-level shock to be on average small across counties. This assumption is likely to be violated in my setting, as the policy instruments are based on state-level R&D tax credits. The instruments may be correlated across multinational firms if the multinational firms' innovation activities in the U.S. are concentrated in certain states (for example, California). Nevertheless, Assumptions Three and Four, weaker versions of Assumptions One and Two (which allow for policy instruments to be correlated and clustered by larger groups, such as headquarter states of multinational firms), may still hold.[40] Finally, I obtain valid and exposure-robust standard errors for the estimated coefficients by running equivalent U.S. multinational firm-level regressions, presented in Table E3.[41] Through these methods, I show that both the first-stage and second-stage results in my main analysis are valid with the exposure-robust inference.

E.3 Alternative Instrumental Variable Construction

In the instrumental variable construction, I first estimate the relation between a firm's innovation and the corresponding user cost of R&D capital at the firm-state level. I then aggregate the predicted patent stocks at the firm level. I find that my findings are robust to an alternative instrumental variable construction process in which I first compute a firm-level weighted average user cost of R&D capital and then use it to predict firm-level patent activities.

I first use the patent stock shares of U.S. firms in each state in 1997, three years before the beginning of the sample period, to construct a firm-level weighted average user cost of R&D capital:

$$\overline{\rho}_{mt} = \sum_{s \in S_m} \rho_{st} \cdot \frac{PatStock_{ms,1997}}{\sum_{s' \in S_m} PatStock_{ms',1997}},$$

in which m denotes each firm, s denotes each state, and S_m denotes the set of states wherein m has conducted innovation activities. ρ_{st} is the R&D tax credit-induced R&D capital user cost in state s in year t.

I then run the following equation to estimate the relation between a firm's patent applications and the weighted-average user cost of R&D capital at the firm level:

$$lnPat_{mt} = \lambda \overline{\rho}_{mt-3} + f_m + f_t + \nu_{mt}.$$

[40] In an unreported analysis, I find that the intra-class correlations are significant at the headquarter-state level but become insignificant at a higher census division level.

[41] As the identification strategy involves non-linear transformation, I cannot replicate the tests in the current setting. I instead first compute the natural log of the multinational firm-level patent stocks and then use the employment shares to aggregate to county-level patent stocks. The alternative measure yields similar results to the baseline and can be transformed into a shock-level variable that can be used to perform the test suggested by Borusyak et al. (2022).

Table E4: Inclusion Restriction Checks for Technological Proximity-based Measures

Dependent variable	$ln(SimpleCounts)$	$ln(CitationWeightedCounts)$
	(1)	(2)
$\overline{\rho}^h_{t-3}$	-11.70***	-15.40***
	(2.523)	(4.657)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Observations	50883	50883

Notes: The table presents the inclusion restriction checks for the alternative instrumental variable, i.e., the predicted patent stocks based on the firm-level R&D capital user costs. The regressions are conducted at the U.S. firm level, with robust standard errors clustered at the firm level. The dependent variable in Column 1 is the natural log of simple counts of patent applications, and the dependent variable in Column 2 is the natural log of citation-weighted counts of patent applications. Each column controls for firm fixed effects and year fixed effects. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

As shown in Table E4, the three-year lagged firm-level weighted average R&D capital user cost significantly reduces the firm's patent application, measured using both simple counts and citation-weighted counts.

Last, I compute the predicted patent counts at the firm level:

$$\widehat{Pat}_{mt} = \exp{(\hat{\lambda}\overline{\rho}_{mt-3})},$$

I calculate the predicted patent stocks using the perpetual inventory method and aggregate the predicted patent stocks following the same procedures as in Section 3.3.

The regression results of my main findings using the alternative IV construction procedure are presented in Table E5. I find that the IV estimates of $PatStock^{loc}$ remain positive and statistically significant. The point estimates are quantitatively larger than the baseline, potentially due to the changes in sample size and the use of a weaker instrument.

Table E5: The Effect of U.S. MNC Innovation on Local Firms' Productivity, Alternative IV

Dependent variable	TFP-LP		Labor productivity	
	(1)	(2)	(3)	(4)
$ln(PatStock^{loc})$	0.444**	0.423**	0.572**	0.543**
	(0.221)	(0.213)	(0.237)	(0.230)
Firm fixed effects	Yes	Yes	Yes	Yes
Industry-year fixed effects	Yes	Yes	Yes	Yes
Ownership type-year fixed effects	Yes	Yes	Yes	Yes
Initial conditions X year dummy	No	Yes	No	Yes
IV test	$F = 14.050$	$F = 14.031$	$F = 14.050$	$F = 14.031$
Observations	214723	214723	214723	214723

Notes: The table presents the regression results of Equation 4 when using the alternative instrumental variable construction. The regression sample includes all local Chinese firms with domestic ownership. The regressions are weighted using the adjusted initial employment of the firms. $PatStock^{loc}$ represents the county-level aggregated patent stocks of U.S. multinational firms. IV estimates are shown in all columns. Each column controls for firm fixed effects, 4-digit Chinese industry–year fixed effects, and ownership type–year fixed effects. Columns 2 and 4 further control for initial local economic conditions interacted with time dummies. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.