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The Local Technology Spillovers of Multinational Firms

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Abstract

This paper identifies the causal effect of U.S. multinationals' technology shocks on their subsidiaries' and nearby domestic firms' productivity in China. By combining firm-level data from both the U.S. and China, I match U.S. multinationals with their manufacturing subsidiaries in China and measure the multinationals' technology shocks to the local firms in China based on the multinationals' patenting activities in the U.S. To address potential endogeneity concerns, I introduce an instrumental variable strategy based on U.S. state-level R&D tax credit policies. I find multinationals' technology improvements induce an increase in the value-added output and total factor productivity (TFP) of both their own subsidiaries and domestic firms in the local areas. The size of the local technology spillover effect depends on local firms' absorptive capacity. I further provide evidence of spillovers through production linkages as well as technological linkages. In addition, spillovers through technological linkages also stimulate innovation of the productive local firms.

Keywords: FDI, technology spillovers, patents, productivity.

JEL codes: D2, F2, O1, O3

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1. Introduction

Foreign affiliates of multinational corporations (MNCs) accounted for 12% of global production in 2014.[2] MNCs' expansion during the past several decades has been accompanied by a lengthy debate over their role in the global economy, particularly in developing countries. In principle, international knowledge diffusion stimulates global economic growth and drives productivity convergence between developing and developed countries (Romer (1993), Coe et al. (1997)). Multinational activities are one of the primary channels through which technology is disseminated globally (Keller (2004)): through the sharing of technology between multinational parents and their foreign subsidiaries, technological advances in multinationals' home countries are then transmitted to foreign destinations (Markusen (2004)). Macro-level evidence (Borensztein et al. (1998)) has also suggested foreign direct investment (FDI) contributes to the economic growth of developing countries. Potential gains from MNCs' technology spillovers have encouraged governments to adopt FDI incentive policies, such as tax incentives, financial subsidies, and regulatory exemptions in many developing countries.

However, the micro-level evidence of technology diffusion through multinational activities remains mixed and inconclusive (Harrison and Rodríguez-Clare (2010)). Previous studies have often documented the impact of FDI inflows on domestic firms in the same industries to be neutral (Haddad and Harrison (1993)) or even negative (Aitken and Harrison (1999)). On the contrary, domestic firms in upstream industries may benefit from FDI inflows through backward linkages (Javorcik (2004)). The role of technology remains obscure in previous literature: horizontally, the potential productivity gains could be offset simultaneously by the competition of multinational entries, while vertically, distinguishing production efficiency improvements from potential supply or demand shocks is difficult.

This paper aims to fill the gaps in the literature by examining the impact of multinationals' technological improvements on their subsidiaries and domestic firms in nearby geographic areas. I first match U.S. public companies with their subsidiaries in China based on the information provided in their annual financial reports (10-K files). I then measure the impact

[2] "Multinational enterprises in the global economy", OECD Report.

of the technology shocks from these parent companies to their subsidiaries based on the citation-weighted patent stocks of the parent companies. I further construct the technology shocks of the MNCs to the domestic Chinese firms in nearby geographic areas as a weighted sum of the parent-subsidiary technology shocks. To address potential endogeneity problems, I adopt an instrumental variable strategy based on state-level research and development (R&D) tax credit policies in the U.S., which induce exogenous shocks to firms' innovation incentives (Wilson (2009), Bloom et al. (2013)). The primary analysis focuses on three sets of outcome variables: value-added output, revenue-based total factor productivity estimated following Ackerberg et al. (2015), and labor productivity measured in terms of value-added per worker.

This paper establishes two main results. First, technological advances of U.S. multinationals are transmitted to their foreign subsidiaries and improve the value-added output and productivity of these subsidiaries. Second, the technology improvements are further transmitted to domestic firms that are geographically close to the subsidiaries, thereby precipitating production expansions and productivity growth of domestic firms. The results validate the existence of both technology transfers from parent companies to their foreign subsidiaries within MNCs, and local technology spillovers from the MNCs to domestic firms. Further discussion reveals the revenue-based productivity improvements are likely to be driven by production efficiency gains rather than price fluctuations. The magnitude of the local technology spillover effect also hinges on local firms' human capital stock, product innovation activities, and ownership types, which are related to the absorptive capacity theory in the management literature (Lane and Lubatkin (1998)).

To advance our understanding of the local technology spillover effects, I further investigate the impact of technology shocks through production linkages. I demonstrate that multinationals' technology shocks lead to production expansions and productivity gains in the domestic firms in both upstream and downstream industries, whereas the effect on firms in the same industry is positive but statistically insignificant. The results suggest multinationals' technological improvements would diffuse to the nearby domestic firms through the production networks, consistent with the findings in the previous literature (Javorcik (2004)).

I further construct measures of technology shocks based on the technological similarity between MNCs and local industries (Hall et al. (2001)), as ordinary industry classification might be insufficient to capture the extent of technology spillovers. I find local firms with closer technological linkages to the multinationals realize higher productivity gains from such spillovers. Technology shocks through technological linkages also stimulate innovation activities of the more productive firms in the local areas.

This paper contributes to the literature on the following grounds. First, it supplements prior studies on the relationship between multinational parents and foreign subsidiaries. Models of multinational production have commonly presumed multinational parents and foreign subsidiaries share common technological inputs (Helpman (1984), Markusen (1995), Helpman (2006), and Antras and Yeaple (2014)). Meanwhile, empirical research has suggested the existence of technology transfers from multinational parents to their foreign subsidiaries in the form of patent royalty transactions (Branstetter et al. (2006)) and that intra-firm technology diffusion further enhances multinationals' sales growth in the foreign market (Keller and Yeaple (2013), Bilir and Morales (2018)). This study complements previous theoretical frameworks and empirical findings by providing direct causal evidence of multinational subsidiaries' productivity gains as a result of their parents' technology advances.

The results also shed light on empirical studies on multinationals' spillover effects. Industry shares of employment and output in foreign-owned firms are frequently used as common proxies of multinational spillovers in the previous literature. Based on those measures, on one hand, studies such as Haddad and Harrison (1993), Aitken and Harrison (1999), Djankov and Hoekman (2000), Konings (2001), Bwalya (2006), and Tao et al. (2017) report that foreign capital inflows exert a minimal or negative effect on the productivity of domestic firms in the same industry;[3] conversely, domestic firms in the upstream industries are likely to benefit from foreign capital inflows, suggested by studies including Javorcik (2004), Kugler (2006), Blalock and Gertler (2008), Javorcik and Spatareanu (2008), Javorcik and Spatareanu (2011), and Gorodnichenko et al. (2014). The classic approach is appealing in that it

[3]For developed countries, however, studies such as Haskel et al. (2007) and Keller and Yeaple (2009) find positive horizontal FDI effects.

reflects the overall impact of multinational activities, but it may also embed challenges for precise interpretation and causal inference of the spillover effects (Keller (2004)). This paper complements the previous studies through the following means. First, rather than relying upon the FDI employment shares, I directly use the parent companies' patent filings to infer potential technological diffusion to their subsidiaries and domestic firms,[4]. Second, I introduce an identification strategy that relies on policy changes in the home countries.[5] Because the R&D tax credit policy in the U.S. is unlikely to be driven by multinationals' performance and foreign market fluctuations, the strategy provides an opportunity to identify the causal effect of multinationals' technology spillovers on the domestic firms in other countries.

Lastly, my analysis also relates to research in the innovation literature. First, studies including Henderson et al. (1993), Peri (2005), Henderson et al. (2005), Thompson (2006), Agrawal et al. (2008), and Murata et al. (2014) illustrate that knowledge spillovers (measured by patent citations) are substantially limited by distance.[6] I incorporate the insights into the paper by restricting my analysis to the domestic firms that are geographically close to the multinational subsidiaries. Second, as discussed in Schmookler (1966), Jaffe (1986), and Griliches (1992), the product-based industry classification system is often insufficient to represent technological boundaries, and the industry technology shocks based on technology linkages adopted in this study improves upon the previous sectoral FDI spillover measures by linking MNCs' knowledge stocks with their relative importance in the Chinese industries. Third, my results also contribute to previous research concerning the real effect of innovation (Jones and Williams (1998), Hall et al. (2010), Hall (2011)) by connecting the innovation outcomes of multinationals with the productivity of the foreign subsidiaries and domestic firms.

The paper is organized as follows: Section 2 introduces the data and construction of key variables. Section 3 outlines the main specification and introduces the identification strategy.

[4] An example of using patent data to measure technology spillovers is Bwalya (2006) in which citation counts are used to infer technology spillovers from Japan to the U.S.

[5] Some recent studies also adopt other identification strategies. For example, Tao et al. (2017) utilizes changes of FDI restrictions in China after 2001 for identification; Abebe et al. (2018) exploits the natural experiment of FDI entry in the local districts.

[6] Macro-level analysis such as Keller (2002) also suggests the benefits from R&D spillovers are decaying over distance.

Section 4 presents the baseline results as well as the related robustness checks and discussion of firms' absorptive capacity. Section 5 examines the technology spillover effects through production linkages and technological linkages, and discusses local firms' response in their innovation activities. Section 6 concludes.

2. Data and Variable Construction

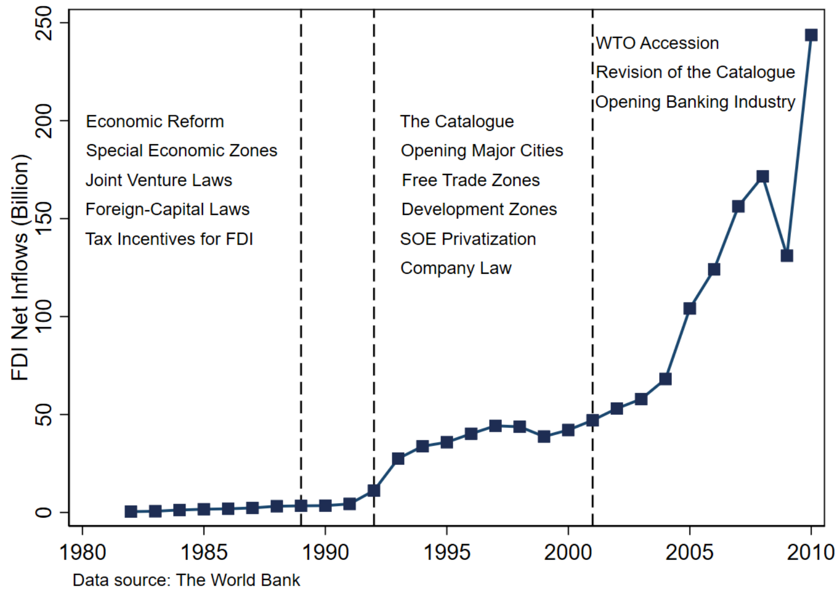
2.1. Institutional backgrounds

The Chinese Economic Reform of 1978 aimed to transform a central government planned economy into a market economy. The reform was initially accompanied by policies that opened certain regions in China to international trade and foreign investment. Since 1980, the government has established several designated economic zones that allow for foreign investment, including cities such as Shenzhen, Zhuhai, Xiamen, Shantou, and the entire Hainan Province. During the 1980s, the Chinese government also passed joint venture laws and foreign-capital laws to support an institutional environment that protects the property rights of foreign investors. The reform was reinforced after 1992, when Deng Xiaoping reaffirmed continuation of the economic reform during his southern tour. Between 1993 to 2000, the government opened major cities such as Beijing and Shanghai to trade and foreign investment and further minimized tariffs and trade barriers. In 1995, the government published the "Catalogue for the Guidance of Foreign Investment Industries" ("the Catalogue"), a guide for the local governments to encourage, permit, restrict, or prohibit FDI in certain classified industries. The industry classification underwent several rounds of revision after 2000. The net inflow of FDI skyrocketed in China after 2001, when the country joined the World Trade Organization (WTO); the figure increased from less than 50 billion in 2001 to about 250 billion in 2010. Figure 1 illustrates the growth of U.S. FDI inflows and the major policy events in China between 1978 and 2010.

U.S. multinationals' FDI in China was initiated early during the Chinese market reform. The U.S. and the People's Republic of China established diplomatic relations in 1979, and in the following several years, numerous U.S. MNCs established their first subsidiaries in

Figure 1: Institutional Background

Notes: This figure shows the change of FDI net flows into China and the corresponding policy changes during the same period. The figure divides the evolution of the institutional changes into three major periods. The first period starts from 1982 to 1989, when China started its market economy reform and opening to trade and FDI. The second period starts from 1992 to 2001, when China deepens the market reform by enriching the ownership laws, opening major cities and trade zones, and starting the privatization process of SOEs. The third period starts from 2001 to 2010, when China accesses WTO and becomes the world's major destination of FDI.



China, including Coca Cola (1979), Pepsi (1981), Johnson & Johnson (1982), and Hewlett-Packard (1985).[7] Although these early entrants often opted for a Chinese headquarters in major cities such as Beijing, Shanghai, and Guangzhou, they have expanded operations to the other cities later. For example, Pepsi first established its headquarters in Beijing in 1981; however, as of 2000, it has established production factories in regional centers such as Changchun, Chongqing, Guilin, Nanchang, and Nanjing. Following the growth of U.S. multinationals' Chinese businesses, the U.S. also became the third largest source country of FDI in China in 2006 (excluding the tax havens) following Japan and South Korea. In 2006, the total amount of FDI inflow added up to 3,061.23 million.[8]

Rich anecdotal evidence has suggested foreign direct investment is likely to introduce technology spillovers to local companies in China. For decades, the Chinese government has

[7]See Table A1 for examples of U.S. multinationals and their entry years.
[8]See Table A2 for the major origins of FDI inflows in China.

been accused of its implicit "technology for markets" policy, under which foreign companies are required to transfer technology to domestic firms to initiate operations in China.[9] Meanwhile, domestic firms may imitate or reverse engineer the products and technology of the multinationals. Foreign companies may also voluntarily share technology with local firms to prevent hold-up problems with local suppliers (Blalock and Gertler (2008)). Technology spillovers may also exist in many other forms, such as labor pooling (Poole (2013)).

2.2. Data sources and variable construction

The Chinese data used in this study are based on the Annual Survey of Industrial Enterprises (ASIE), which are collected by the Chinese National Bureau of Statistics (NBS) and includes all state-owned enterprises (SOEs) and non-SOEs with annual sales of over 5 million Chinese yuan (about $604,600 in 2000). The data contains basic information of each company, including name, location, industry, ownership structure, and starting year; and performance variables, such as gross output, value added, net income, fixed assets, intermediate inputs, and employment. Some items that are uncommon in standard financial statements are also reported in the ASIE, including value of export, value of new products, and employee compensation. I primarily focus on two sets of key firm-level outcome variables: value-added output and revenue-based productivity measures (total factor productivity and labor productivity). Value-added output is constructed directly based on the data using the logarithm of the reported values, deflated by industry price indices. I further estimate a two-factor production function (Ackerberg et al. (2015)) with value added as production output and employment and capital as production inputs,[10] to estimate the revenue-based total factor productivity (TFPR).[11] I also construct labor productivity defined by log value-added output per worker as well as other firm-level outcome variables from the data, including wage, return on assets (ROA), intangible assets, and value of exports. The other Chinese data sources used in this study include Chinese patent data from the State Intellectual Property Office (SIPO), which contains patents granted to individuals and firms

[9] See, for example, Jiang et al. (2018).

[10] I follow Brandt et al. (2017) to construct capital stocks using perpetual inventory method.

[11] The estimation procedure is outlined in later sections and in the appendix.

by the SIPO between 1990 and 2015.[12]

In terms of U.S. data sources, I mainly rely upon patent data from the Harvard Patent Network Dataverse, which was 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, and contains both information concerning each patent applicant, including names, states, and assignee numbers, as well as the characteristics of each patent, including technology class, application year, and grant year. Furthermore, the database also includes every pair of cited and citing patents, which is used to construct citation measures. I use the crosswalk provided by Kogan et al. (2017) to link each patent to U.S. publicly listed companies, and the annual Compustat data to access U.S. public firms' other financial information.

2.3. Matching U.S. public firms to their Chinese subsidiaries

Recent research in both economics and finance has exhibited increasing interest in exploiting the textual data of firms' financial reports to garner information not presented in financial statements.[13] For example, Hoberg and Moon (2017) and Hoberg and Moon (Forthcoming) use 10-K filings to determine companies' exposure to off-shoring activities and relate such measures to these public companies' stock market performance. This paper expands the existing approaches that utilize financial reports by extracting exact parent-subsidiary information from the 10-K files. Relative to other potential data sources for identifying parent-subsidiary linkages, [14] the current study directly constructs the relationship based on publicly accessible financial reports and can be combined with rich firm-level panel data from both the U.S. and China.

The matching of U.S. public companies with their Chinese subsidiaries involves both automated textual search algorithms and hand-matching. I primarily use the annual 10-K files from the Securities and Exchange Commission (SEC) database to construct these relation-

[12]The data were recently used in studies such as Bombardini et al. (2017).

[13]For example, Hoberg and Phillips (2010) and Hoberg and Phillips (2016) construct 10K-based product similarity measures; Loughran and McDonald (2011) construct 10K-based measures of tones, and Bodnaruk et al. (2015) construct a 10K-based measure of financial constraints.

[14]Branstetter et al. (2006), Keller and Yeaple (2013), Bilir and Morales (2018) use the within-company transaction records from confidential data of 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 China's Ministry of Commerce.

ships. The 10-K files are annual U.S. public firm financial reports required by the SEC, and they include not only standard financial statements, but also rich textual information about the companies' operations and outcomes. I first download all 10-K files from the SEC Edgar database and then identify the U.S. firms that mention related keywords in their 10-K files through text scraping. Specifically, I define the U.S. firms as related if their 10-K files include the words "China" or "Chinese" plus "subsidiary," "operation," "facility," "investment," or "venture" in the same sentence. I also randomly select about 50 financial reports to validate my search. The validation results confirm the searching algorithm targets the companies with various forms of operations in China.

Of these potential candidate firms, I manually examine the Exhibit 21 tables (list of subsidiaries) in the 10-K files to extract the detailed names and locations of their Chinese subsidiaries if they exist. When the Exhibit 21 tables are missing or do not contain any Chinese subsidiary information, I also examine the main text of the 10-K files to search for the related keywords and record the exact forms of these firms' operations in China. A large proportion of these firms report sales offices, representatives, or business partners in China rather than manufacturing subsidiaries. I also supplement my list of subsidiaries from 10-Ks with an additional list of Chinese subsidiaries of U.S. companies from the ORBIS database, which exclusively contains currently operating subsidiaries. I exclude from the list the subsidiaries that were initiated after 2000. I demonstrate that the ORBIS data adds 25 more U.S. public firms and 42 additional subsidiaries to my final matches, which indicates my 10-K-based method of identifying subsidiaries of U.S. public firms captures a major proportion of possible matches.

I then manually match these subsidiaries (both from 10-Ks and ORBIS) with the ASIE data one by one. The names are often not precisely identical after translation into Chinese; I therefore use keyword searches in multiple search engines to determine the names and information of the subsidiaries. For each potential match, I also investigate the name, location, industry, starting year, and ownership information to ensure the match is correct.[15]

Lastly, I restrict my focus to the subsidiaries from between 2000 and 2007 to eliminate

[15]Figure A.1 shows my name-matching procedure using Pepsi Co. as an example.

selection problems, because the entry and exit decisions of the subsidiaries could be correlated with innovation shocks from the U.S. parents. I also restrict the parent companies of these subsidiaries to the U.S. companies that exist (and are not acquired) between 2000 and 2007 in the Compustat data.

Of all 4,918 U.S. public companies that existed between 2000 and 2007, about 20% are associated with China-related keywords, and I discover 224 U.S. public firms that include subsidiary information that can be matched to the ASIE data. I examine the main text of 10-Ks of the other firms and determine that a substantial proportion of them have discussed their sales office, representatives, or business partners in China when referring to the related keywords. Therefore, I am unlikely to overlook a substantial number of U.S. public firms' subsidiaries due to missing information in the 10-Ks. Including firms from the ORBIS data and restricting them to subsidiaries starting before 2000 changes the numbers to 235 U.S. public firms and 452 subsidiaries in China. Finally, matching with the patent data reduces the number of public firms to 210 and the number of subsidiaries to 325 because some of the U.S. public firms did not file any patents or were not matched to the patent database. Because I could not distinguish between the two, I eliminate these firms from my final match.[16]

As of year 2000, the largest MNC in the linkage is Motorola Solutions Inc., which employed over 13,000 people total and experienced sales of over 34 billion yuan (over 4 billion U.S. dollars) in 2000. Notably, most of the matched MNCs are in high-tech industries, such as electronics (Motorola, Flextronics, Emerson), machinery (United Technologies, General Electric, Cummins), and chemistry (DuPont and Procter & Gamble).[17]

2.4. Measuring technology stocks

Measuring technology shocks is based on patent stocks of U.S. public firms. I utilize the Harvard Patent Dataverse to compute the citation-weighted patent counts, and use the crosswalk provided by Kogan et al. (2017) to match the patents with the Compustat public firms.

[16] Table A3 presents the matching rate for each step.

[17] Table A4 presents the top 15 U.S. MNCs in size from the final match.

The truncation problem presents a classic challenge of using the patent counts and citation counts (Hall et al. (2001)): when closer to the final year of the patent data, the patent counts are downward-biased due to the absence of applied patents that have not yet been granted, and the citation counts are also downward-biased because of the missing citations from patents granted after the final year. I address the truncation problem by implementing Hall et al. (2001) and Hall et al. (2005)'s quasi-structural approach that estimates the empirical distribution function of both patent counts and citation counts for each of the six technology categories and adjusts the counts in later years using the deflators based on the estimation results.[18]

I apply the perpetual inventory method with a 15% depreciation rate, as suggested in the previous literature,[19] to construct the patent stock measures:

$$K^P_{mt} = (1-\eta)\mathrm{K}^P_{mt-1} + P_{mt}.$$

In the equation above, m denotes U.S. MNCs and t denotes years varying from 1975 to 2010; K^P is the cumulative patent stock, and P_{mt} is m's citation-weighted patent counts in the application year t. I primarily use citation-weighted patent stock to measure technology levels of U.S. public firms because the weighting scheme accounts for the importance of each patent.

I use parent company m's three-year lagged patent stock as a proxy for the potential technology transfers from m to its foreign subsidiary n:

$$TECH^{sub}_{mnt} = Log(K_{mt-3}).$$

After identifying the domestic firms that locate in the same county of the subsidiaries, I measure local technology stocks as a weighted sum of the subsidiary-level technology stocks, with the initial share of subsidiaries' employment in each county as weights:

$$TECH^{loc}_{ct} = log(\sum_{n \in N_c} K_{m(n)t-3} \cdot \frac{w_{n0}}{W_{c0}}).$$

[18]The detailed adjustment procedure is outlined in the appendix.
[19]See, for example, Hall et al. (2005), Matray (2014). An alternative choice is to use a 10% depreciation rate as in Keller (2002) and Peri (2005).

In the equation above, N_c is the set of all matched subsidiaries in county c, $K_{m(n)t-3}$ is n's parent company $n(m)$'s patent stock at year $t-3$, w_{n0} is the initial employment of n, and W_{c0} is the total employment of firms in county c in the initial year. In other words, I use the employment share of n in county c as weights to compute the aggregated county-level technology stocks of MNCs. I use the time-invariant weights to avoid potential endogeneity problems due to technology-induced changes in subsidiary sizes. The local technology stocks measure serves as a proxy for the potential technology spillovers from the subsidiaries to the domestic firms in the same county.

The measure of local technology stocks can be rationalized through a simple model in which local technology diffusion is realized by the connections between workers in the multinationals and local firms. I first assume each U.S. subsidiary n with size L_n is embedded with technology level T_n from their parent company m. In each period, x percent of employees of n have contact with any other workers in the local firms with equal probability.[20] Assuming the local economy is of size L, each worker in the local firm has an equal probability of $x \cdot \frac{L_n}{L}$ having contact with the employees of n and of benefiting from the knowledge spillovers of size T_n. The technology spillovers that originated from subsidiary n are therefore $x \cdot T_n \frac{\cdot L_n}{L}$, and the overall local technology spillovers are $x \cdot \sum_{n \in N_c} \frac{T_n \cdot L_n}{L}$. By replacing the technology level T_n with lagged citation-weighted patent stock K_{mt-3} and size L_n with the initial level of employment s_{n0}, the formula coincides with the construction of local technology stocks.

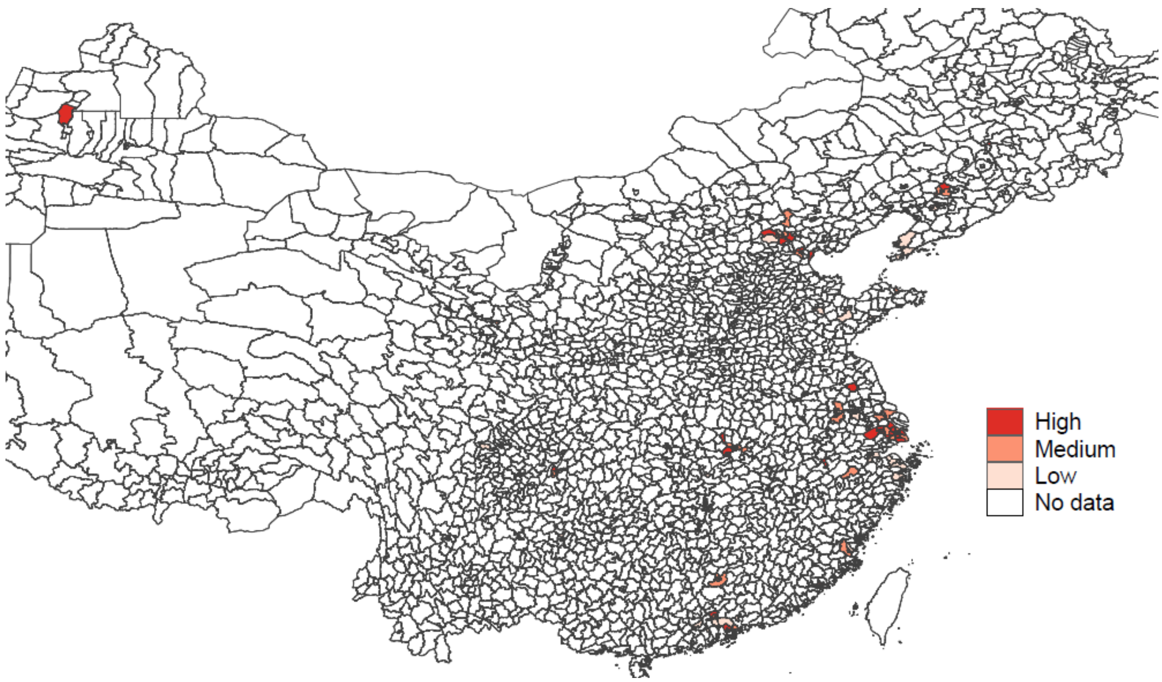
Figure 2 illustrates the geographic distribution of $TECH^loc$ in 2000. Many of the affected counties are clustered around the four largest cities, namely, Beijing, Shanghai, Guangzhou, and Shenzhen, as well as more developed provinces, such as Jiangsu, Zhejiang, and Guangdong. However, the influence of the MNC subsidiaries is also disseminated nationally: many of the subsidiaries are located in the northeast, southwest, and central part of China, and some of these subsidiaries are also linked to the most innovative U.S. parent companies.

I begin with this general measure that reflects the potential local technology spillovers on all manufacturing firms in nearby counties, which facilitates an understanding of the overall impact of the multinationals' innovation activities on the local economy. Section 5 constructs

[20] Alternatively, assume in each period that x percent of multinationals' employees randomly flow from those multinationals to the local firms.

Figure 2: Geographic distribution of $TECH^{loc}$ in 2000

Notes: This figure shows the geographic distribution of the measured technology spillover, which is the 3 year lagged log weighted sum of citation-weighted patent stock of the subsidiaries' U.S. parent firms. The subsidiaries are located in 121 counties out of 2280 in total. On average the matched subsidiaries account for 7.3% of the total employment and 19.0% of the total output of the counties where they located.



industry-specific measures of local technology stocks based on subsidiaries' industry codes and technological relationships between the multinationals and local firms.

2.5. Productivity estimation

The primary outcome variables of the analysis include local firms' value-added output (va), revenue-based total factor productivity ($tfpr$), and labor productivity (lb). Because the construction of value-added output and labor productivity is straightforward, this section briefly introduces the construction of TFPR.

Directly measuring firms' production efficiency ($tfpq$) based on the ASIE data is infeasible due to the lack of exact input and output price data at the firm level. As such, I have instead estimated the revenue-based total factor productivity ($tfpr$) and discussed the effects on $tfpq$ under specific assumptions.

I mainly apply Ackerberg et al. (2015) method (henceforth the ACF method) to measure firm-level TFPR. First, I assume the following "value-added" Cobb-Douglas production function:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \pi_{it} + \epsilon_{it}.$$

In this function, y_{it} represents the value of the value-added output, k_{it} represents capital, and l_{it} represents total employment. Two components constitute the residual term: the persistent factor, π_{it}, and the idiosyncratic factor, ϵ_{it}, which consists of transitory shocks and measurement errors. The value-added production function assumes gross output is Leontief in the intermediate input m_{it}; therefore, the intermediate input is proportional to the gross output.[21]

I estimate the production function based on the ACF two-stage method.[22] In the first stage, I estimate the output function using a 3-order polynomial of l, k and m, controlling for a set of fixed effects and, most importantly, a set of multinationals' technology stock variables constructed in the previous sections, as suggested by Pavcnik (2002). In the second step, I implement the generalized method of moments (GMM) estimator to recover the coefficients for capital and labor at the same time. The estimated TFPR is therefore $\hat{\pi}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}$.

2.6. Summary statistics

Table 1 displays the summary statistics of the key variables in the analysis. Panel A includes the sample of all matched subsidiaries of the U.S. public firms, and panel B includes the sample of all local firms in the matched Chinese counties. Panel C indicates the distribution of the technology-shock measures. Comparing panel A with panel B demonstrates that the matched subsidiaries are larger in size and more productive than local firms in nearby geographic areas. The matched subsidiaries are, on average, 975% of the annual sales of the domestic firms, 246% of the total employment of the domestic firms, and 200% of the TFP of the domestic firms. The subsidiaries also pay 216% higher wages to their employees and export much more than the local Chinese firms, on average. The differences persist after

[21]The value-added production function assumption is discussed in, for example, Bruno (1978), Diewert (1978), and Levinsohn and Petrin (2003).

[22]the detailed estimation procedure is outlined in the appendix.

Table 1: Summary statistics

Variables	*Mean*	*Median*	*Std. Dev.*	*N*
Panel A. Matched subsidiaries				
Value added (millions RMB)	199.59	4.83	1125.30	1,957
Gross output (millions RMB)	673.03	165.56	3857.75	1,957
TFPR	2.41	2.85	2.14	1,957
Labor productivity	5.17	5.58	2.14	1,957
Employment	496.43	203.00	1045.79	1,957
Wage (thousands RMB)	48.07	37.75	36.05	1,957
Export value (millions RMB)	267.18	14.60	2250.20	1,957
Panel B. Local firms				
Value added (millions RMB)	17.93	4.03	224.52	226,097
Gross output (millions RMB)	69.39	16.42	757.15	226,097
TFPR	1.42	1.65	1.78	226,097
Labor productivity	3.82	4.01	1.74	226,097
Employment	202.83	86.00	643.17	226,097
Wage (thousands RMB)	15.20	12.43	10.42	226,097
Export value (millions RMB)	4.49	0.00	166.36	226,097
State ownership (%)	21.80			226,097
Collective ownership (%)	19.40			226,097
Private ownership (%)	58.80			226,097
Panel C. Technology shocks				
Parent-subsidiary tech. shocks	7.80	8.27	2.64	1,957
Local tech. shocks	2.85	3.16	3.47	226,097
Within-industry shocks	0.56	1.3	3.85	24,512
Shocks to upstream	-2.18	-1.98	3.85	185,393
Shocks to downstream	-2.15	-1.9	3.5	187,827
Tech.-distance based shocks	0.97	1.17	3.44	222,403

Notes: The table presents the summary statistics of key variables in the main analysis, in which panel A presents the characteristics of matched subsidiaries, panel B presents characteristics of local firms in the matched counties, and panel C presents the distribution of technology shock measures. The units are noted in the parentheses, if necessary.

controlling for county, industry, and ownership fixed effects. These substantial differences not only validate our matches of U.S. subsidiaries, but also indicate the subsidiaries may induce sizable technology spillovers for local firms, as the subsidiaries are not only large in size, but also technologically advantageous relative to local firms.

3. Specification and Identification Strategy

3.1. Specification

I estimated the effect of technology shocks exerted by parent companies on their foreign subsidiaries (the intra-firm technology transfer effect) and the effect of local technology shocks on domestic firms (the local technology spillover effect) using the following fixed effect models, respectively:

$$Y_{nt} = f_n + f_t + \theta^{sub} TECH^{sub}_{nt} + X_{nct} + \epsilon^{sub}_{nct};$$
$$Y_{ict} = f_i + f_t + \theta^{loc} TECH^{loc}_{ct} + \epsilon^{loc}_{ict}.$$

In these equations, n denotes matched subsidiaries, i denotes local Chinese firms, c denotes counties, and t denotes years. Y refers to the outcome variables, and X_{ct} refers to the control variables. I include firm fixed effects to control for any time-invariant firm characteristics. I also control for year fixed effects to capture any common shocks to all firms during the year. The general year fixed effect is further divided into industry-year fixed effects to absorb any industry-specific shocks, such as industry supply or demand shocks in each year, and ownership-year fixed effects, which are intended to absorb any ownership-specific shocks, such as the SOE reforms in the 2000s. The robust standard errors are clustered at the parent company level in the parent-subsidiary technology transfer specification, and the robust standard errors are clustered at the county level in the local technology spillovers specification. The regressions are weighted using the initial employment of the firms for the following reasons: First, the weighting scheme controls for the heteroskedasticity in the initial firm size (Greenstone et al. (2010)); second, the estimated coefficients of the regression results can be interpreted as "per capita" effects; third, the weighting scheme is also consistent with the conceptual framework of knowledge transfer through worker connections or worker flows. The coefficients of interest are θ^{sub} and θ^{loc}. θ^{sub} represents the estimated parent-subsidiary technology transfer elasticity, and θ^{loc} represents the estimated local technology spillover elasticity.

The OLS estimates could suffer from endogeneity problems, such that $cov(TECH^{sub}, \epsilon^{sub}) \neq 0$ (patent stocks of multinationals correlate with unobserved shocks that affect subsidiaries' outcomes) or $cov(TECH^{loc}, \epsilon^{loc}) \neq 0$ (multinationals' technology stocks correlate with unobserved shocks that affect local firms' outcomes). First, as in the classic simultaneity problem (the "correlated effect" as in Manski (1993)), MNC headquarters, foreign subsidiaries, or local Chinese firms could respond simultaneously to identical unobserved shocks. In the parent-subsidiary technology transfer specification, a negative bias could be caused by CEO's limited attention[23]; that is, if CEOs occasionally allocate attention from foreign operations to domestic research and development centers, the increase in innovation outcomes in the U.S. will be associated with the contraction of foreign operations, thereby creating a negative bias in the OLS estimates. In the local technology spillover specification, a bias could result from unobserved supply or demand shocks. For example, an unobserved positive global supply shock that enhances both local Chinese firms' performance and multinationals' innovation outcomes would create a positive bias in the OLS estimates. Conversely, an unobserved shift in tastes toward multinationals' products (or high-quality products) in the global market that also reduces the market demand for the Chinese products would produce a negative bias in the OLS estimates.

The second source of bias relates to the sorting behaviors of the multinational subsidiaries. Specifically, the innovation capacity of the multinationals may correlate with their unobserved ability to select subsidiary locations, thereby resulting in bias in OLS estimates. This type of bias could be either positive or negative: if multinationals prefer locations with lower expected wages and input cost growth, and if more innovative multinationals are superior in selecting the preferred locations for their subsidiaries, the bias would be negative; conversely, if multinationals prefer locations with higher levels of human capital stocks and faster market-demand growth, the bias would be positive.

To address potential endogeneity issues, I first restrict the sample of subsidiaries to those initiated before 2000 so that the entry decisions are unlikely to be affected by the multinational parents' innovation activities during the sample period. I further introduce an instrumental variable strategy based on the U.S.'s R&D tax credit policies in the following section.

[23]See, for example, Schoar (2002) and Seru (2014), for empirical evidence of CEO limited attention.

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 parts: the federal tax credit system and the state tax credit system. The federal R&D tax credit was first introduced in the *Economic Recovery Tax Act of 1981*. The policy grants a 25% tax credit for all qualified research and development expenses (QRE) defined by the U.S. Internal Revenue Code (IRC).[24] Since 1981, Congress had extended the R&D tax credit policy multiple times, and made it permanent in 2015.

The introduction of the state R&D tax credit policies closely align with that of the federal policy, and the state tax codes typically apply the same QRE definition as the federal government. In 1982, Minnesota became the first state to introduce the state R&D tax credit. As of 2007, 32 U.S. states have introduced some form of the R&D tax credit, and Hawaii, Rhode Island, Nebraska, California, and Arizona have the highest effective credit rate, ranging from 11% to 20%.

The effective state R&D tax credit rates commonly change over the course of years due to policy adjustments.[25] Figure 3 illustrates the changes in these tax credits from 1994 to 2001 (the duration of my analysis), and displays significant variation in state-level R&D tax credit policy adjustments. Furthermore, the impact of the tax credits on firms' research and development investment may also correspond with macroeconomic fluctuations and other tax policy changes, such as interest rates and corporate income tax rates. To adjust for these factors, I use the state-specific, R&D tax credit-induced user cost of research and development capital (henceforth, user cost of R&D capital), constructed following Hall (1992), Wilson (2009), and Bloom et al. (2013) in my instrumental variable construction.[26]

3.3. Instrumental variable construction

I construct the instrumental variable in four steps. First, I compute each firm's patent stock in each state in year 1997, which corresponds to the starting year of the three year

[24]The three main components of eligible research expenses are: wages; supplies; contract research expenses, as in the 2005 IRC section 41. Please see Audit Techniques Guide: Credit for Increasing Research Activities for the detailed definition.

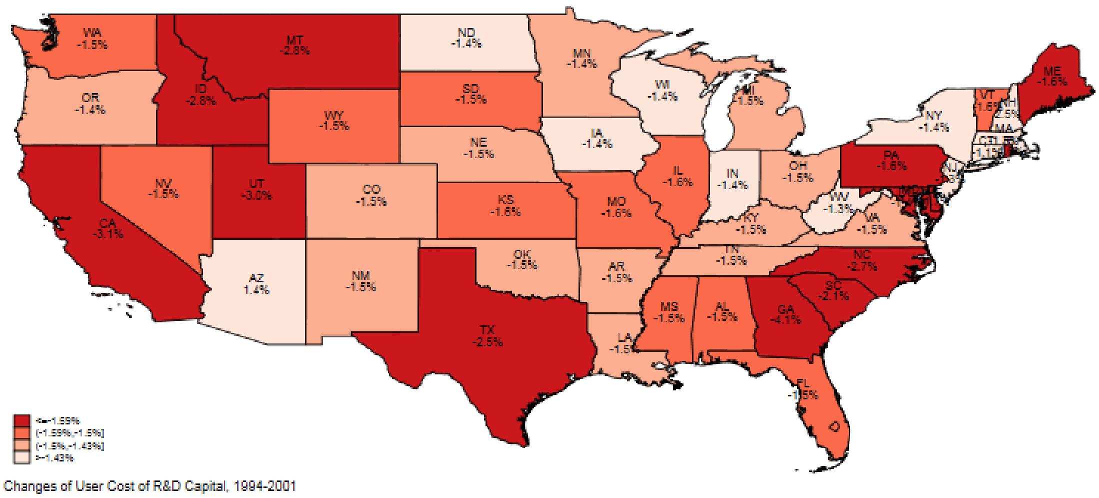
[25]For example, Arizona changes its tax credit rate from 20% to 11% in year 2001.

[26]The formula to construct the user cost of R&D capital is presented in the appendix.

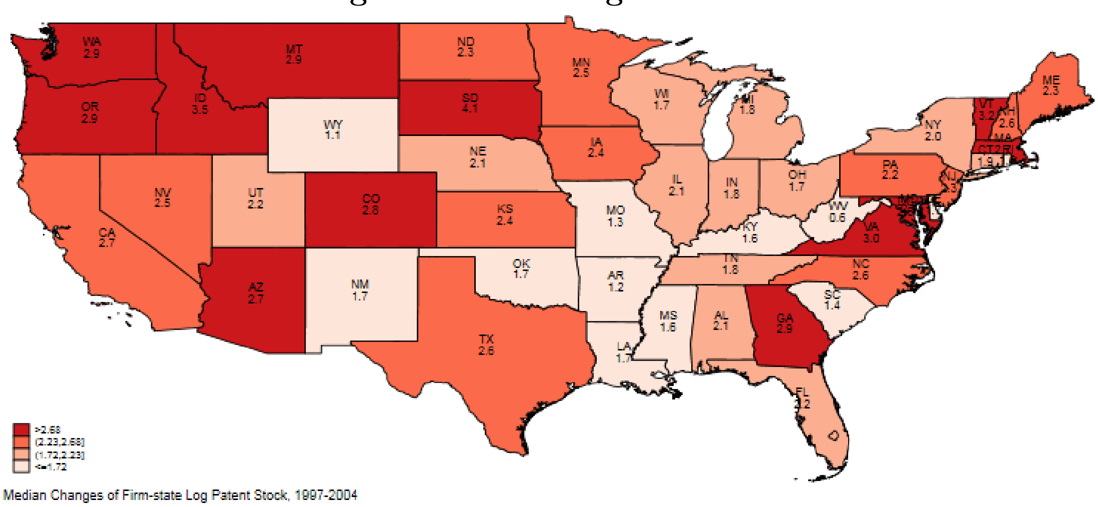
Figure 3: Changes of R&D Capital User Cost and Median Log Patent Stock

Notes: The figures show the geographic distribution of the changes of R&D capital user cost and median log patent stock. The upper figure shows the change of R&D capital user cost from 1994 to 2001, and the lower figure shows the change of median firm-state log patent stock from 1997 to 2004, corresponding to the time period in our main analysis.

Change of R&D Capital User Cost



Change of Median Log Patent Stock



lagged measures of technology stocks. The patent stock share in each state is a proxy of the geographic distribution of the firm's innovation activities. Based on the state-specific average user cost of R&D capital, I compute the firm-specific user cost of R&D capital as:

$$\tilde{\rho}_{it} = \sum_{s \in S} w_{is} \rho^h_{st},$$

where ρ^h_{st} is the user cost of R&D capital for the highest tier of R&D spending firms in state s and year t, and w_{is} is firm i's share of citation-weighted patent stocks in state s and year 1997.

I further compute a cumulative R&D user cost (similar to my patent-stock construction) as:

$$Z^{sub}_{it} = \sum_{t'=t_{i0}}^{t} (1-\eta)^{t'-t_{i0}} log(\bar{\bar{\rho}}_{it'}),$$

where t_{i0} is the starting year of firm i, $\eta = 15\%$ is the depreciation rate of knowledge capital, and $\bar{\bar{\rho}}_{it'}$ is the average firm-level user cost of R&D capital from $t'-3$ to t'. The coverage of three years before the patent application year is to account for research durations.[27]

The firm-specific cumulative user cost of R&D capital is directly used as the instrument for the technology transfers from the U.S. parents to their subsidiaries. The first-stage regression specification in identifying the parent-subsidiary technology transfer effect is written as:

$$TECH^{sub}_{nt} = f_n + f_t + \lambda^{sub} Z^{sub}_{m(n)t-3} + \nu^{sub}_{nt},$$

where I control for subsidiary fixed effect f_n and year fixed effect f_t, with standard errors clustered at the parent company level. λ^{sub} is the coefficient of interest, which represents the elasticity of the parents' patent stocks in response to the cumulative log R&D capital user costs.

Next, I compute the weighted average of the user costs at the Chinese county level, based on the initial size of the subsidiaries in China:

$$Z^{loc}_{ct} = \frac{\sum_{n \in N_c} Z^{sub}_{m(n)t-3} \cdot w^0_n}{\sum_{n \in N_c} w^0_n},$$

in which w^0_n is the initial employment of subsidiary n, and N_c is the set of all matched subsidiaries in c. The term can be interpreted as the average cumulative R&D user cost of the parent companies of all foreign subsidiaries in the county.

The first-stage regression specification in identifying the local technology spillover effect

[27] In the appendix, I show the cumulative R&D user cost construction is an approximation of a constant elasticity relationship between patent counts and R&D user cost.

is represented as:

$$TECH^{loc}_{ict} = f_i + f_t + \lambda^{loc} Z^{loc}_{ct-3} + \nu^{loc}_{ict}.$$

The first-stage regression would be conducted at the Chinese local firm level, where f_j is the firm fixed effects, and f_t is the year fixed effects, which could be further replaced by sector-year fixed effects and ownership-type-year fixed effects. As in the previous equation, λ^{loc} is the coefficient of interest, representing the elasticity of local technology stocks of multinationals in response to the average cumulative log R&D capital user cost changes.

Table 2: First-stage Regressions

First-stage regressions, 2000-2007				
Dependent variables	$\widehat{TECHsub}$		$\widehat{TECHloc}$	
	(1)	(2)	(3)	(4)
Z^{sub}	-2.316***	-2.272***		
	(0.640)	(0.620)		
Z^{loc}			-0.991***	-0.992***
			(0.208)	(0.188)
Local controls	No	Yes		
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	No	No	Yes	No
Sector-year fixed effects	Yes	Yes	No	Yes
Ownership-year fixed effects	No	No	No	Yes
Sample	Subsidiaries		Local firms	
Observations	1,957	1,957	226,097	226,097
R-squared	0.982	0.982	0.9937	0.994

Notes: The table presents the first-stage regression results for the parent-subsidiary technology transfer specification and the local technology spillovers specification. Robust standard errors are clustered at parent company levels in columns 1 and 2, and at county levels in columns 3 and 4. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 2 displays the first stage regressions. The results show the constructed instruments exert negative effects on the corresponding multinational technology shocks, which are both economically and statistically significant. The F-statistics of the first-stage regressions are at least around 10, which is the lower bound of strong instruments, as suggested by Stock and Yogo (2002).[28]

[28] In the appendix, I discuss how the identification strategy of using the cumulative user cost of R&D capital might fulfill the criteria of the exclusion and inclusion restrictions in detail.

4. Technology Transfers and Local Technology Spillovers

4.1. Parent-subsidiary technology transfers

I examine the relationship between parent companies' innovation and their subsidiaries' performance. This step serves as a validation assessment because the existence of the parent-subsidiary technology transfers is necessary for the multinationals' local technology spillover effect. Additionally, the question concerning whether technology advances of the parent companies are transmitted to their foreign subsidiaries is worth investigating in itself. Previous studies have documented substantial technology transfers within multinationals (Branstetter et al. (2006)). A parallel strand of literature has established that productivity shocks of parent firms could be transmitted to their foreign subsidiaries (for example, Boehm et al. (2019), Bilir and Morales (2018)). However, few studies have yet investigated whether technological improvements in parent companies also generate productivity gains in their foreign subsidiaries.

I begin by studying how the matched subsidiaries' log value-added output, TFPR, labor productivity, and markups are affected by their parent companies' three year lagged citation-weighted patent stocks ($TECH^{sub}$). I control for firm fixed effects that eliminate any time-invariant subsidiary characteristics and industry-year fixed effects that absorb industry specific shocks in each year. I further include the mean sales, TFPR, and markups level of the local firms in the same sector and county of each matched subsidiary in the regressions to control for the local economic conditions. Last, as previously discussed, I weight each firm by its initial employment level and cluster the robust standard errors at the parent company level.

Table 3 presents the regression results. Column 1 suggests a 10% increase in the parents' lagged patent stocks is associated with a 2.8% increase in the subsidiaries' value-added outputs. As indicated in Column 2, controlling for the local economic conditions did not eliminate the positive correlations between the parents' lagged patent stocks and the subsidiaries' value-added outputs. The IV estimate using the cumulative user costs of research and development capital as instruments in Column 3 indicates a 10% increase in the parents' lagged patent stocks causally increases the value-added outputs of the subsidiaries by 5.8%.

In Column 3 relative to Column 2, the IV estimate is approximately double the OLS estimate, which may either be due to attenuation bias (because the standard error also becomes larger) or unobserved factors, such as CEO attention, as discussed previously. Column 4 shows the TFPR is also positively correlated with the parents' technology shocks, but the OLS estimate presents negative bias (compared with Column 5). Columns 5 and 6 suggest a 10% increase in the parents' lagged patent stocks causally increases the revenue-based productivity measures, including TFPR and labor productivity, by about 3.6% to 3.8% respectively.

Table 3: Effects of the parent-subsidiary technology shocks

Parent-subsidiary technology transfers						
Dependent variables	*va*	*va*	*va*	*tfpr*	*tfpr*	*lp*
	(1)	(2)	(3)	(4)	(5)	(6)
Models	OLS	OLS	IV	OLS	IV	IV
$TECH^{sub}$	0.279***	0.307***	0.579***	0.213**	0.380**	0.362**
	(0.0929)	(0.104)	(0.198)	(0.0888)	(0.163)	(0.171)
Local controls	No	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stats			15.594		15.594	15.594
Observations	1957	1957	1957	1957	1957	1957
R-squared	0.767	0.769	0.767	0.692	0.691	0.682

Notes: The table presents the regression results of the effects the parent-subsidiary technology shocks. Regressions are weighted using the initial employment of the firms. Robust standard errors are clustered at the parent company level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

I also investigate how the other firm-level outcomes of the subsidiaries respond to the parent companies' technology stocks.[29] I find subsidiaries' average wage and return on assets respond to the technology shocks at 10% significance level.

4.2. Local technology spillovers

The results presented in the previous subsection confirm that the subsidiaries of the U.S. multinationals benefit from technological advances of their parent firms. The next question is to ask whether the local firms in China also benefit from the technological improvements of the multinationals in the local areas. This subsection addresses this question by examining

[29] See Table A8.

how the local firms' log value-added output, TFPR, and labor productivity, are affected by the multinationals' local technology shocks ($TECH^loc$), which is measured in terms of the log weighted sum of lagged patent stocks. I control for firm fixed effects and year fixed effects (or industry-year and ownership-year fixed effects) in the regressions, and weight the regressions in terms of the initial employment of firms. Robust standard errors are clustered at the county level.

Table 4: Effects of the local technology shocks

Local technology spillovers						
Dependent variables	*va*	*va*	*va*	*tfpr*	*tfpr*	*lp*
	(1)	(2)	(3)	(4)	(5)	(6)
Models	OLS	OLS	IV	OLS	IV	IV
$TECH^{loc}$	0.214**	0.201*	0.331*	0.169**	0.249**	0.242**
	(0.104)	(0.108)	(0.181)	(0.0835)	(0.116)	(0.117)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
Industry-year FE	No	Yes	Yes	Yes	Yes	Yes
Ownership-year FE	No	Yes	Yes	Yes	Yes	Yes
First-stage F-stats			27.866		27.866	27.866
Observations	226097	226097	226097	226097	226097	226097
R-squared	0.707	0.719	0.719	0.615	0.615	0.606

Notes: The table presents the regression results of the effects the local technology shocks. Regressions are weighted using the initial employment of the firms. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 4 presents the regression results. Column 1 shows a 10% increase in the local technology stocks is associated with a 2.1% increase in the local firms' value-added outputs, and the magnitude changes to 2.0% after controlling for industry-year and ownership-year fixed effects rather than year fixed effects in Column 2. Column 3 shows a 10% increase in the local technology stocks causally leads to a 3.3% increase in the value-added outputs of the local firms at 10% significance level. Similar to the previous results, the IV estimate is approximately twice as large as the OLS estimate, suggesting a negative bias due to either attenuation bias, or the global shocks as previously discussed. Column 4 shows the TFPR is also positively correlated with the local technology stocks, but the OLS estimate is negatively biased (when compared with Column 5). As shown in Columns 5 and 6, a 10% increase in the local technology stocks also causally increases local firms' revenue-based productivity measures by 2.4% to 2.5%.

I also investigate the effect of the local technology stocks on the other outcomes of local firms,[30] and find the local firms' average wage and intangible assets are responding positively to the local technology stocks at 10% significance level. Furthermore, the local technology shocks also improve the survival rate of the more productive firms.[31].

4.3. Magnitudes

I discuss the implied magnitudes of the identified effects in the baseline regressions in detail. First, one within-firm standard deviation in the parent-subsidiary technology transfers (0.372) leads to a 21.5% increase in the subsidiaries' value-added outputs, a 14.1% increase in the subsidiaries' TFPR, and a 13.5% increase in the subsidiaries' labor productivity. The one-standard-deviation effect of the parent-subsidiary technology transfers on TFPR explains about 9.0% of the within-firm TFPR variations in the matched subsidiaries.

Meanwhile, one within-firm standard deviation in the local technology spillovers from the U.S. multinationals (0.221) leads to a 7.3% increase in the local firms' value-added outputs, a 5.5% increase in the local firms' TFPR, and a 5.3% increase in the local firms' labor productivity. The one-standard-deviation effect of the local technology spillovers on TFPR explains approximately 4.87% of the within-firm TFPR variations in the matched subsidiaries. Additionally, the intra-firm effect of technology shocks is more substantial than the inter-firm one. The difference could be driven by firm boundaries that impede the transfer of technology from multinationals to domestic firms.

4.4. Robustness Checks

This section provides a list of robustness checks to address various potential concerns regarding the baseline results.

In the primary analysis, I have made one seemingly arbitrary assumption: I presume the duration of international technology diffusion through multinationals is three years. I examine alternative choices regarding the duration of technology spillovers.[32] I find the parent-subsidiary technology transfer effects are significant at the 5% level for lagged years

[30] See Table A9.
[31] See Table A10.
[32] The results are shown in Figure A.6

from one to three, and the local technology spillover effects are significant at 5% for lagged years from zero to four, so the baseline results are robust to various alternative choices of lagged years. Furthermore, I also check whether the outcomes of the subsidiaries and local firms respond to technology shocks in the future years. I find, unsurprisingly, that the coefficients are both small in magnitude and statistically insignificant at the 5% level.

I then exploit the effects of the other shocks originating from multinationals' activities, which naturally results in an examination of the impact of R&D-based spillovers. Because the constructed instruments can be directly applied to the R&D stocks of the multinationals, I was able to investigate the causal impacts of the R&D stocks on the subsidiaries' and local firms' outcomes. As expected, I find the effect of R&D-based technology shocks is highly similar to the effect of the patent-based technology shocks and that an increase in multinationals' R&D stocks precipitates productivity growth among the subsidiaries and the local firms.[33]

I further examine the impact of multinationals' sales and employment shocks on the subsidiaries. Due to the lack of valid instruments, I was only able to study the correlations between the shocks and subsidiaries' performance. I document that subsidiaries' outputs are positively associated with both employment growth and sales growth among their parent companies, but productivity is not significantly affected.[34]

Previous studies using employment or output share measures have found mixed evidence of multinational technology spillovers. To display the differences between the "size" shocks in the previous studies and the "technology" shocks constructed in this paper, I also compute the shares of employment and value-added output shares of foreign-owned enterprises in the local areas and examine the correlation between those size shocks and the performance of the local firms (excluding the foreign-owned enterprises themselves). I find the measured size shocks are negatively correlated with local firms' outcomes such as value added output and TFP.[35] The results reveal substantial differences between the impacts of technology shocks and size shocks.

[33] See Table A13.
[34] See Table A14.
[35] See Table A15.

I use alternative TFPR and markup measures estimated based on trans-log production function, which approximates constant elasticity of substitution (CES) production functions. I find my baseline results persist under the alternative production functions,[36] and thus the estimated productivity gains of the subsidiaries and local firms unlikely result from mis-specified production functions.

To further validate my baseline results, I investigate how the U.S. firms collectively (including their subsidiaries) respond to parent companies' innovation in the U.S. I first construct outcome variables of U.S. public firms based on the Compustat database, including log employment, log sales, TFPR, and labor productivity. I then regress these firm-level outcomes on their three-year lagged patent stocks for all U.S. public firms matched to the patent data, instrumented using the firm-level cumulative log user costs of R&D capital. The results suggest the overall levels of employment, sales, TFP, and labor productivity of the U.S. public multinationals all respond positively to their lagged patent stocks at 5% significance level.[37] The finding is consistent with previous studies finding the strongly positive private returns to R&D investments (Hall et al. (2010)), implying the growth in firms' knowledge stocks generate real returns in the forms of sales growth and productivity gains.

The hypothesized diffusion process of MNCs' technology shocks consists of two steps: The first step involves technology transfers from U.S. parent companies to their subsidiaries in China; the second involves technology spillovers from the subsidiaries to the local firms. However, direct technology spillovers from U.S. parent companies to the local Chinese companies remain possible, for example, through outsourcing contracts directly from the U.S. parent companies. In other words, if U.S. multinationals obtain enhanced knowledge regarding the local business environment in China from their subsidiaries and outsource their production to these local Chinese companies, the positive local technology spillover effect identified in our baseline regression might result from those outsourcing activities rather than learning from the subsidiaries. To address this concern, I interact the local technology

[36] See Table A16

[37] See Table A17.

shock measures with the share of initial employment of outsourcing MNCs.[38] The results indicate that, the technology shocks from the outsourcing U.S. companies are unlikely to be the driving force of the positive local technology spillover effect identified in our baseline regressions, because increasing shares of outsourcing multinationals in the local areas do not significantly alter the magnitude of the local technology spillover effects.[39]

4.5. Absorptive Capacity

Previous literature on FDI spillovers has found the spillover strength is contingent upon local firms' absorptive capacity, namely, the ability "to recognize the value of new, external information, assimilate it, and apply it to commercial ends" (Cohen and Levinthal (1990)). Griffith et al. (2004) have revealed the multifaceted role of R&D investment of both stimulating innovation and enhancing technology transfer. Blalock and Gertler (2009) note that firms with more innovation activities, larger technology gaps with the MNCs, and more educated workers would benefit more from FDI spillovers. In line with these studies, this section investigates the role of local firms' absorptive capacity in the channeling of MNCs' technology shocks. Specifically, it examines how the effect of MNCs' technology shocks depends upon the following factors: ex-ante wage levels, introduction of new products, and ownership types.

I first investigate whether firms' human capital stocks magnify the impact of technology spillovers. Because the typical measures of human capital stocks (e.g., education levels) are not observed in the data, I use firms' average wage levels as a proxy for human capital stocks. I define the high-wage (high human capital) firms as those with average wage above the median level in the corresponding two-digit industry-year groups. I then interact the indicator variable with the local technology spillover measure. The regression results are shown in Columns 1 and 2 of Table 5. I find the estimated effects on value-added output and TFPR are significantly higher for firms with higher wage levels, suggesting human capital might be associated with firms' ability to absorb external technology diffusion. However, because wage is not a sufficient measure of human capital, further research is necessary to

[38]I identify outsourcing U.S. companies based on the match provided by Hoberg and Moon (Forthcoming).
[39]See Table A18.

identify the role of human capital in channeling technology spillovers.

Table 5: Determinants of absorptive capacity

Determinants of absorptive capacity						
Dependent variables	*va*	*tfpr*	*va*	*tfpr*	*va*	*tfpr*
Characteristics (X)	*wage*		*product innovation*		*private ownership*	
	(1)	(2)	(3)	(4)	(5)	(6)
$TECH^{loc}$	0.289	0.198*	0.232	0.195*	0.392**	0.275**
	(0.177)	(0.114)	(0.201)	(0.113)	(0.195)	(0.113)
$TECH^{loc} \times X$	0.108***	0.133***	0.218***	0.119***	0.0302	0.0279*
	(0.0251)	(0.0264)	(0.0477)	(0.0293)	(0.0204)	(0.0151)
Observations	226097	226097	226097	226097	226097	226097
R-squared	0.718	0.611	0.717	0.613	0.717	0.614

Notes: The table shows the determinants of local firms' absorptive capacity. Iv coefficients are reported in all columns. Firm fixed effects and industry-year fixed effects are controlled in all columns, and ownership-year fixed effects are controlled for columns 1 to 4. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

I then examine the role of innovation activities in local firms' responsiveness to the multinationals' technology spillovers. Because ASIE only contains R&D expenditure data for years after 2005, I alternatively measure firms' innovation activities using the sales of new products. [40] I define the innovative firms as those with positive sales of new products in any year during the sample period. Columns 3 and 4 of Table 5 suggest that the estimated effects on value-added output and TFPR are significantly different for the innovative firms and their non-innovative counterparts, implying innovation activities play a crucial role in local firms' absorption of the external technology diffusion from the multinationals.

Last, I examine how firms with different ownership types might respond differently to technology spillovers. Previous studies on the Chinese economy, such as Hsieh and Klenow (2009), suggest firms' ownership structures are associated with mis-allocations of production inputs. Particularly, state-owned enterprises (SOEs) in China are less productive but larger relative to other ownership types, and this inefficiency might affect SOEs' response to external technology spillovers. Columns 5 and 6 of Table 5 suggest that private firms realize higher productivity gains than SOEs, but the difference is only statistically significant at the 10%

[40] The variable is also used in Tao et al. (2017) to measure innovation activities.

level and the magnitude of the difference is minor. In summary, the results in this section illustrate that absorptive capacity of local firms hinges on multiple factors, including innovation activities, average wage levels, and ownership types. The findings may be explained by the previous theories concerning the determinants of firms' absorptive capacities.

5. Production and Technological Linkages

The general measure of multinationals' local technology stocks enables an understanding of the overall impact of the multinationals' technology improvements on the local economy (manufacturing firms), but the local technology spillover effect also varies by the relationship between the multinationals and local firms. This section extends the previous local level measure of technology shocks into two county-industry specific measures: The first assesses technology shocks based on the production linkages between the multinational subsidiaries and the local firms, while the second assesses technology shocks based on the technological linkages between the multinational subsidiaries and local firms.

5.1. Production linkages

I first investigate how the firms within the same industry, or in the upstream or downstream industries of the subsidiaries, respond to the local technology spillovers of multinationals. The analysis is inspired by the previous studies that exploit the size shocks of multinationals. Conventional wisdom suggests that the inflow of foreign capital intensifies competition in the industry and suppresses domestic firms' productivity growth as their fixed costs of production are now spread over a smaller market (Aitken and Harrison (1999)), and benefits the upstream industries either through increasing product standards or technology transfer (Javorcik (2004)). However, the effect of the multinationals' technology shocks may differ for the following reasons. First, the quality upgrades associated with the technology improvements may precipitate market segmentation between the multinationals and local competitors and generate a weaker competitive effect relative to the size shocks. Second, some of the general-purpose technologies (GTS) may also spread to downstream and upstream industries, thereby producing forward and backward effects. To investigate the effects of multinationals' local technology shocks through industry relationships and to further understand the differences between technology shocks and size shocks, I construct the within-industry technology shocks and the associated shocks to upstream and downstream industries. I first construct a measure of industry-level local technology spillovers as:

$$TECH_{cst}^{within} = log(\sum_{n \in N_{sc}} K_{m(n)t-3} \cdot \frac{w_n^0}{W_{cs}^0}),$$

in which s denotes industries, N_{sc} is the set of matched subsidiaries in county c and industry s, and W_{cs}^0 is the total employment in county c and industry s.

I then construct measures of industry-level local technology spillovers as:

$$TECH_{cst}^{upstream} = log(\sum_{s' \in U_s} \bar{K}_{cst-3} \cdot a_{ss'}),$$

$$TECH_{cst}^{downstream} = log(\sum_{s' \in D_s} \bar{K}_{cst-3} \cdot b_{ss'}).$$

$\bar{K}_{cst-3} = \sum_{n \in N_{sc}} K_{m(n)t-3} \cdot \frac{w_n^0}{W_{cs}^0}$ is the multinationals' lagged patent stocks in industry s and county c, U_s is the set of upstream sectors of sector s and D_s is the set of downstream sectors of s, and $a_{ss'}$ ($b_{ss'}$) is industry s''s share of input (output) in sector s. The construction process of upstream/downstream shocks closely follows the previous studies, using input-output table coefficients to weight the industry-level measures.

I regress local firms' outcomes, including value-added outputs, TFPR, and labor productivity, on the within-industry and upstream or downstream technology spillovers, controlling for firm fixed effects, industry-year fixed effects, and ownership-year fixed effects, and clustering the standard errors at the county-industry level.

Table 6 presents the baseline results. Panel A shows the estimated within-industry effects of technology spillovers. I find the value-added outputs, TFPR, and labor productivity respond positively to the technology spillovers, but only the effect on value-added outputs is significant at 5% level. A one-within-firm-standard-deviation increase in the within-industry technology spillovers causally increases the local firms' value added outputs by 5.3%. Panel B shows the estimated effects of technology spillovers to the upstream industries. I find the effects on the upstream firms' value-added outputs productivity to be both positive and statistically significant. A one-within-firm-standard-deviation increase in the backward technology spillovers leads to a 12.7% increase in value-added output, a 7.8% increase in

Table 6: Technology shocks through input-output linkages

Panel A. Within-industry technology shocks			
Dependent variables	*va*	*tfpr*	*lb*
	(1a)	(2a)	(3a)
$TECH^{within}$	0.205**	0.148	0.149
	(0.0888)	(0.100)	(0.0955)
First-stage F stats	38.261	38.261	38.261
Observations	21833	21833	21833
R-squared	0.712	0.635	0.633
Panel B. Technology shocks to upstream			
Dependent variables	*va*	*tfpr*	*lb*
	(1b)	(2b)	(3b)
$TECH^{upstream}$	0.678**	0.408**	0.365**
	(0.306)	(0.187)	(0.167)
First-stage F stats	17.936	17.936	17.936
Observations	164063	164063	164063
R-squared	0.740	0.635	0.632
Panel C. Technology shocks to downstream			
Dependent variables	*va*	*tfpr*	*lb*
	(1c)	(2c)	(3c)
$TECH^{downstream}$	0.500**	0.398***	0.389***
	(0.197)	(0.128)	(0.129)
First-stage F stats	19.793	19.793	19.793
Observations	166236	166236	166236
R-squared	0.741	0.632	0.629

Notes: The tables shows the effects of local technology shocks on the local firms' performance through industry linkages. Panel A reports the estimated effects withinin-industry, Panel B reports the estimated effects to the upstream industries, and panel C reports estimated effects to the downstream industries. IV coefficients are reported in all columns. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered two-way at the county level and industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

TFPR, and a 6.9% increase in labor productivity. Similarly, as shown in panel C, the local technology spillover effects to the downstream industries on domestic firms' value-added output and productivity are also positively significant, and a one-standard-deviation increase in the forward technology spillovers leads to a 9.5% increase in value-added output, a 7.6% increase in TFPR, and a 7.4% increase in labor productivity.

The results first confirm the existence of cross-industry technology spillover effects. In addition to the spillovers through backward linkages as often found in the previous studies, I also find evidence supporting spillovers through forward linkages. Because local firms are more likely to form production relationships with the subsidiaries, the effects could consist of both directed technology transfers and learning-by-doing.

Meanwhile, local firms in the same industry still benefit from the technology spillovers in terms of their production scale, but the effects on productivity are much weaker. The difference between the within-industry effect and cross-industry effect could be explained by the fact that multinational subsidiaries are more willing to share knowledge with their suppliers and buyers rather than their local competitors. Nevertheless, the evidence also shows that, unlike FDI inflows, the technology improvements of multinationals do not directly result in a dominant product competition effect at the local level.

5.2. Technological linkages

The industry-specific local technology stocks based on the subsidiaries' industry codes might suffer from shortcomings. First, many of the multinationals and their subsidiaries are conglomerates that operate across multiple industries, and are embedded with diversified technology stocks; therefore, single-industry classifications might undermine the potential technology shocks to firms in the related industries.[41]. Second, industry classification is generally product based rather than technology based, while the applications of certain technology often occur across industries (Jaffe (1986)). Therefore, measuring the technology shocks of multinational subsidiaries based on their industry classifications may be insufficient.

To improve the traditional measure of multinational spillovers based on industry linkages between the multinational subsidiaries and the local firms, I instead exploit the technological linkages. As the first step, I classify the patent stocks of U.S. firms into six technological categories defined in Hall et al. (2001) and Hall et al. (2005): Chemical, Computers & Communications, Drugs & Medical, Electrical & Electronic, and Mechanical.[42] In other words, for each U.S. company j, I denote its technology stock by a five dimensional vector

[41] For example, P&G (China) serves "over a billion Chinese consumers with more than 20 brands across nine categories" (PG in Greater China) In the ASIE data, its headquarter industry code is 2671, Soup and Detergent production.

[42] Patents that do not belong to any of the categories are dropped from the data.

$\vec{K}_{jt}^P = (K_{jt}^{P,1}, K_{jt}^{P,2}, ..., K_{jt}^{P,6})$, in which $K_{jt}^{P,\kappa}$ denotes firm j's patent stock in technological category κ. Next, using the SIPO database merged with ASIE,[43] I classify the Chinese patents into the five technological categories as well, and compute the percentages of patent stocks in each technological category for each Chinese industry: $\vec{p}_s = (p_{s1}, p_{s2}, ..., p_{s5})$, where $p_{s\kappa}$ denotes the share of patent stocks of technological category κ in industry s. To avoid simultaneity problems, I use the patent stocks of year 2000, the beginning year of my analysis, to compute the shares. I then compute an industry-specific local technology spillover measure based on the technology similarities between MNCs and Chinese industries:

$$TECH_{sct}^{dist} = log\Big(\sum_{\kappa \in \{1,2,...,5\}} p_{s\kappa} \big(\sum_{n \in N_c} K_{n(m)\kappa t-3}^P \cdot \frac{w_{ij0}}{W_{c0}} \big) \Big),$$

in which $p_{s\kappa}$ is the share of parents from technology category κ in industry s, N_c is the set of all matched subsidiaries in county c, and $K_{m(n)\kappa t-3}^P$ is subsidiary n's parent company m's citation-weighted patent stocks in technology category κ. w_{ij0} and W_{c0} are the same as previously defined.

The ideal measures of technological closeness are based on more detailed technology classification systems (the measure used in Jaffe (1986) or the Mahalanobis extension used in Bloom et al. (2013)), or the pairwise technology linkages based on citations between MNCs and local firms (Branstetter (2006)). Applying those methods to the current analysis faces several obstacles. First, although categorizing the technology codes in SIPO (International Patent Classification, or IPC) into the five technological categories is straightforward and clear, the mapping between the IPC and the CPC (Cooperative Patent Classifications, the classification system adopted by USPTO), could be complicated and inaccurate, making implementing the Jaffe (1986) method unfavorable. Second, only a limited number of Chinese inventors cite U.S. patents when filing patent applications, making the use of the citation-based measures of technology linkages implausible.

I assess the impact of multinationals' industry-specific shocks through technological linkages by regressing the firm-level outcomes (value-added outputs and TFPR) on the newly constructed measures of technology shocks based on the technological linkages. As in the

[43] The match is based on the linkage provided by He et al. (2018).

previous analysis, I control for firm fixed effects, industry-year fixed effects, and ownership-year foxed effects. In addition, I examine the within-county variations of technology shocks by incorporating county-year fixed effects. Because the industry-specific local technology shocks vary by both county and industry, robust standard errors are two-way clustered at the industry level and the county level.

Table 7: Technology shocks through technological linkages

Local spillovers through technological linkages						
Dependent variables	*va*	*va*	*tfpr*	*tfpr*	*lp*	*lp*
	(1)	(2)	(3)	(4)	(5)	(6)
$TECH^{dist}$	0.328**	0.335*	0.300**	0.362**	0.307**	0.382**
	(0.158)	(0.172)	(0.138)	(0.175)	(0.138)	(0.183)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
Ownership-year FE	Yes	Yes	Yes	Yes	Yes	Yes
County-year FE	No	Yes	No	Yes	No	Yes
First-stage F-stats	37.267	50.282	37.267	50.282	37.267	50.282
Observations	222316	222316	222316	222316	222316	222316
R-squared	0.748	0.768	0.649	0.673	0.642	0.665

Notes: The tables shows the effects of local technology shocks on the local firms' performance through technological linkages. IV coefficients are reported in all columns. Robust standard errors are clustered two-way at the county level and industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 7 presents the results. The local technological linkage-based measure causally increases the local firms' value-added outputs and TFPR: a one-standard-deviation increase in the technology spillovers leads to a 9.5% increase in the value-added outputs and a 9.8% increase in the TFPR (labor productivity) of the local firms that are technologically linked to the multinationals. The magnitudes of the estimated effects are bigger than the baseline estimates and significant at the 5% level. Furthermore, I find the positive effects persist after controlling for the county-year fixed effects, suggesting the positive local technology spillovers are mainly attributed to the within-county differences in technological closeness between the local firms and the multinationals, and the local firms with similar technological patterns absorb the technology diffusion from the multinational subsidiaries.

As an alternative to the traditional industry linkage based spillover measures, the technological linkage based measure of the local technology shocks encapsulates multinationals' technology spillovers on the local firms, suggesting stronger causal effects on the local firms' outputs and TFPR, and reflects that the within-county variance originated from technological closeness between local firms and multinational subsidiaries is the main driver of the positive spillover effects. I further apply the measure to study the spillover effect on local firms' innovation decisions.

5.3. Innovation Activities

This section investigates the effect of the multinationals' technology shocks on local firms' innovation activities. Specifically, it examines how local firms' patenting activities respond to the technology shocks based on the SIPO patent data combined with the ASIE. A local technology shock might exert two potential effects on local firms' choices of innovation status. First, the productivity gains from the technology spillovers may stimulate the local firms to implement greater innovation if the quality improvements from innovation complement the productivity gains in firms' profit.[44] Second, technology improvements among the multinationals might also induce local firms to imitate or specialize in low-end production processes[45] that diminishes their innovation inputs. The second factor can be interpreted as a reduction in the fixed costs of adopting "low-type" technologies (e.g., imitation or low-end production technologies).[46] Intuitively, new product design and production processes adopted by multinational subsidiaries are likely to lower the information barriers of imitation or reverse engineering among non-invention firms; competition from the multinationals' high-quality products may also induce the local firms to specialize in low-quality products. If the two channels (the productivity-gain effect and the fixed-cost-reduction effect) both exist in the local technology spillovers, the effect of local technology shocks on the local firms' innovation will be heterogeneous across firms. For the less productive firms, the technology shocks will weakly improve or even deter their innovation activities while the positive effect on innovation will be stronger among more productive firms.

The empirical analysis primarily focuses on firms that filed at least one patent in SIPO

[44]Such relations are presented in, for example, De Loecker (2011).

[45]For example, Arkolakis et al. (2018) present a model featuring international specialization in innovation (in the developed countries) and production (in the developing countries).

[46]A simple framework is provided in the appendix.

Table 8: Effects of technology shocks on innovation

Technology shocks and patent filings				
Dependent variables	*Log(Invention + utility patents)*		*Log(Invention patents)*	
	(1)	(2)	(3)	(4)
$TECH^{dist}$	0.0781	0.0656	0.0816	0.0707
	(0.0641)	(0.0623)	(0.0498)	(0.0484)
Lagged TFP	0.00747***	0.00494*	0.00298	0.000783
	(0.00280)	(0.00278)	(0.00219)	(0.00226)
$TECH^{dist} \times \mathbb{1}(HighTFP = 1)$		0.0215**		0.0186**
		(0.00869)		(0.00843)
Observations	166230	166230	166230	166230
R-squared	0.856	0.855	0.868	0.867

Notes: The table shows the effects of multinationals' technology shocks on the local firms' innovation activities. IV results are reported in all columns. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the county-industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

between 2000 and 2007. I construct two measures of local firms' innovation outcomes: first, log stocks of invention and utility model patents and second, log stocks of solely invention patents.[47] Conceptually, the measures include the patents that effectively reflect technological improvements. I regress the two innovation outcomes on the measured local technology spillovers, the lagged TFP levels, and the interaction of the measured local technology spillovers with an indicator with value 1 if and only if the firms' TFP is higher than the industry median level in the last year:

$$K_{ict}^{P} = f_i + f_t + \beta_1 TECH_{ct}^{loc} + \beta_2 TFP_{it-1} + \beta_3 TECH_{ct}^{loc} \times \mathbb{1}(HighTFP = 1) + \epsilon_{ict},$$

and the previous discussion predicts that $\beta_1 \approx 0$ and $\beta_3 > 0$.

Table 8 displays the regression results. Columns 1 and 3 show that the overall effect of the local technology spillovers on firm-level innovation is positive but statistically insignificant.

[47] China has three main types of patents: invention patent, utility model patent, and design patent. By definition, an invention patent refers to "any new technical solution relating to a product, a process or improvement"; a utility model patent refers to "any new technical solution relating to the shape, the structure, or their combination, of a product"; and a design patent refers to "any new design of the shape, the pattern or their combination, or the combination of the color with shape or pattern, of a product". For details, see SIPO official website: FAQ.

In Columns 2 and 4, I interact the technology spillover measure with the indicator of high TFP levels. Consistent with the predictions, the results imply the effect of technology spillovers on innovation activities is positive and statistically significant for the high TFP groups. I find that compared with the less productive firms, more productive firms respond to a one-within-firm-standard-deviation increase in technology shocks by increasing their invention patents by 0.55%, and the combination of invention and utility model patents by 0.64%.

6. Concluding Remarks

Based on a unique match between U.S. public firms and their manufacturing subsidiaries in China, as well as a novel identification strategy, this study provides new empirical evidence on international knowledge transfers from parent companies to their foreign subsidiaries and then to local domestic firms, resulting in both production expansion and productivity gains of the subsidiaries and local firms in China.

I further investigate the underlying channels of the technology spillovers from multinationals to the local firms. Consistent with conventional wisdom, I find the local technology spillovers are stronger across industries rather than within industries. I further find the local spillovers are largely explained by the technological relationships between the multinationals and local firms. The strength of the spillover effect is also contingent upon the absorptive capacity of the local firms, in the form of innovation activities, human capital stocks, and ownership types. Multinationals' technology spillovers also accelerate the innovation process of the productive firms in the local areas.

This study suggests several directions for future research. First, a similar approach of matching U.S. multinationals with their subsidiaries in foreign countries could be applied to investigate MNCs' spillover effects in other countries. Comparing the technology spillover effects between developed and developing countries might shed light on the current research. Second, whether the technology diffusion from the multinationals to the local firms harms the multinationals is unclear. Because many of the debates concerning the current trade war between the U.S. and China have focused on "technology stealing" by Chinese firms, evaluating the consequences of multinational technology spillovers for U.S. firms themselves is necessary. Lastly, the approach of obtaining subsidiary information from U.S. public companies' financial reports can be extended to gather more information concerning headquarters' exact foreign investment decisions, such as establishing new plants, having joint investments with local companies, and acquiring or selling subsidiaries. Such knowledge will potentially foster opportunities for natural experiments and case studies that may shed light on the FDI literature.

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Appendix A Truncation Adjustment

Following Hall et al. (2001), we adjust the citation-weighted patent counts to alleviate the truncation problems. The Harvard patent dataverse contains all patents granted by USPTO before 2010. There are two types of truncation problems. First, with respect to patent counts, patents filed before 2010 but granted after 2010 are not included in the data. Second, with respect to citation counts, citations made after 2010 are not included in the data. As our analysis focuses on the patent data up to 2007, the two types of truncation problems might lead to sizable bias in my estimates.

I adjust the citation-weighted patent counts in two steps. First, I compute the following empirical cumulative probability distribution function:

$$F^P(s) = \frac{\sum_t \sum_{t'=t}^{t+s} P_{t,t'}}{\sum_t P_t}$$

where P_t denotes total number of patents filed in year t, and $P_{t,t'}$ denotes the number of patents filed in year t and granted in year t'. In words, I compute the proportion of patents that are granted within s years after filed. I estimate the function for each of the six technological categories[48]. I also restrict the estimation sample to the patents filed between 1970 and 2000 to avoid the truncation problem. I replace $F(s) = 1$ for $s > 10$, as the estimation results show that $F(s)$ is greater than 99% for $s > 10$ for any technological category. The first step aims to adjust the truncation problem associated with patent numbers.

In the second step, I use the quasi-structural method to adjust citation counts. Following Hall et al. (2001) and Hall et al. (2005), I estimate the following equation:

$$log(C_{tt'}/P_t) = \alpha_0 + \alpha_t + \alpha_{t'} + f(L)$$

in which $C_{tt'}$ is the number of citations made at year $t' > t$ on patents filed in year t, P_t is the number of patents filed in year t, L denotes the year lags $t' - t$, and

$$f(L) = \log(exp(-\beta_1 L)(1 - exp(\beta_2 L)))$$

[48] The six technological categories are: Chemical, Computers&Communications, Drugs&Medical, Electrical&Electronic, Mechanical, and Others.

I apply nonlinear least-squares models to estimate $beta_1$ and $beta_2$ for each technological category, and compute the predicted cumulative probability function (net of filing year and application year fixed effects) as:

$$F^C(s) = \sum_{L=0}^{L=s} exp(-\hat{\beta}_1 L)(1 - exp(\hat{\beta}_2 L))$$

for s up to 30.

In the final step, I adjust the patent weighted patent counts P_t^C field at year t by

$$P_t^{C,adjusted} = \frac{P_t^C}{F^P(2010 - t) \cdot F^C(2010 - t)}$$

Appendix B Variable Definition and Data Cleaning

1. Value-added: It is 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. Employment: number of employees are directly reported in the ASIE data. I replace 0 values using 1.

3. Capital: I use perpetual inventory method following Brandt et al. (2017) to construct real capital measures. I replace the non-positive values using the minimum positive value within each 2 digit industry-year group.

4. Wagebill: wage-bill is directly reported in the ASIE data. To be consistent with the other variable constructions, I replace wagebill using value-added if wagebill is larger than value-added.

5. Wage: average wage is computed using $Wagebill/employment$.

Appendix C Productivity Estimation

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

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

where y_{it} is value-added output, k_{it} is capital input, l_{it} is labor input, $\omega_i t$ is the persistent productivity term, and ϵ_{it} is the transitory productivity shocks. I assume that the production function parameters, β_k and β_l, vary by two-digit industry codes. In other words, the production function is estimated separately for each two-digit industries.

Following Levinsohn and Petrin (2003) and Ackerberg et al. (2015), I assume that firms' intermediate input demand is expressed as:

$$m_{it} = \tilde{f}(k_{it}, l_{it}, X_{it}, \omega_{it})$$

where X_{it} are a set of control variables elaborated later

Substitute the inverted intermediate input demand function, $\omega_{it} = \tilde{f}(k_{it}, l_{it}, X_{it})$ into the production function gives:

$$y_{it} = \beta_k k_{it} + \beta_l l_{it} + \tilde{f}(k_{it}, l_{it}, X_{it}) + \epsilon_{it} = \tilde{\Phi}(k_{it}, l_{it}, X_{it}) + \epsilon_{it}$$

In the first step of our estimation, I estimate the predicted output function $\tilde{\Phi}$ with a third-degree polynomial of k_{it}, l_{it}, and $X_{it} = (e_{it}, MTCH_{it}, SPL^{loc}_{it}, Z_{it})$. In detail, I include:

1. interaction terms of k_{it} and l_{it} up to the third degree;
2. an export dummy e_{it}, and its interactions with with all terms in 1;
3. an indicator variable of whether the firm is in a county with matched U.S. subsidiaries $MTCH_{it}$, and its interactions with with all terms in 1;
4. the measure of local technology spillovers SPL^{loc}_{it}, and its interactions with with all terms in 1;
5. 4-digit industry fixed effects, ownership fixed effects, and province fixed effects (Z_{it}).

For each set of values (β_l, β_k), the estimated productivity is expressed as:

$$\hat{\omega}_{it} = \hat{\Phi}_{it} - \beta_k k_{it} - \beta_l l_{it}$$

In the second step, I assume that the law of motion of ω could be written as:

$$\omega_{it} = \alpha_0 + g(\omega_{it-1}) + \alpha_e e_{it} + \alpha_m MTCH_{it} + \alpha_s SPL_{it}^{loc} + \xi_{it}$$

where $g(\cdot)$ is a fourth-order polynomial function, and I estimate the parameters (β_l, β_k) using generalized method of moments (GMM) with the following moment conditions:

$$\mathbb{E}\left(\xi_{it}(\beta)\begin{pmatrix} 1 \\ l_{it} \\ k_{it-1} \\ \hat{\hat{\Phi}}_{it-1}(k_{it}, l_{it}, X_{it}) \end{pmatrix}\right) = 0$$

Last, I estimate TFP as the residual term from the production function:

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

Appendix D Details of R&D Tax Credit

R&D tax credit plays a key role in the U.S. economy and corporate innovation activities. In 2015, the total R&D expenditure is about $495 billion in the U.S. About 70%, or $355 billion came from private sector. The total R&D expenditure accounts for about 2.7% of total GDP, and the private sector R&D accounts for about 1.9%[49]. Government support for business R&D expenditures account for 0.25% of total GDP in the U.S. in year 2015, and about 30% of the funding (0.07% of GDP) is in the form of tax incentives[50]. Therefore the amount of government support accounts for about 13% of total business R&D expenditures, and the tax incentives account for about 4%.

The common form 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 year 2000, California provides an R&D tax credit of 15% for qualified research expenses (henceforth, QRE). The amount of R&D tax credit is computed in the following steps[51]:

[49]See Fact Sheet–Research & Development by the Numbers, R&D Coalition.
[50]See Measuring Tax Support for RD and Innovation, OECD.
[51]Detailed illustration and examples are provided in An Overview of California's Research and Development Tax Credit.

1. Step 1: Identify current-Year qualified RD expenses.
2. Step 2: Calculate 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 1984 through 1988, capped by 16%.
3. Step 3: Calculate RD base amount. The R&D base amount is computed as the average annual gross receipts in the last three years multiplied by the base-period percentage.
4. Step 4: Calculate R&D tax credit. It is computed by the excess amount of the current-year qualified R&D expenses over the base amount multiplied by the tax credit rate (15%).

and I further provide a simple numerical example in Table A6. I use Microsoft as an example and assume all 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 the previous literature, 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 from 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 and f denotes federal level variables; r_t is the real interest rate, δ is the economic depreciation rate of R&D capital, τ's are effective corporate tax rates, z_t is the present discounted value of tax depreciation allowance, and s is the share of R&D expenditures that qualifies for special tax treatment.

Appendix E Demonstration of Instrument

I denote patent stocks as K, patent counts as P, and the user cost of R&D capital as r. I assume that $K = \sum_{s=0}^{\infty}(1-\delta)^s P_s$, in which P_s is the patent counts s years before the current period; and $P_s = C \cdot r_s^{\epsilon}$, in which ϵ is the elasticity of patent counts in response to the user cost of R&D capital.

I further assume a steady state level of innovation: (K_0, P_0, r_0), in which $K_0 = \sum_{s=0}^{\infty}(1-\delta)^s P_0 = P_0/\delta$, and $P_0 = C \cdot r_0^{\epsilon}$.

Now consider a deviation of r_s from the steady state level r_0. Let $\tilde{r}_s = log(r_s)$, and applying Taylor expansion gives:

$$\begin{aligned}\log(K(\tilde{r}_s) - \log(K_0) &= (1-\delta)^s \frac{P_0 \cdot \epsilon}{K_0} \cdot (\tilde{r}_s - \tilde{r}_0) \\ &= (1-\delta)^s \frac{P_0 \cdot \epsilon}{K_0} \cdot (\log(r_s) - \log(r_0))\end{aligned}$$

Therefore the following approximation holds:

$$\frac{\partial K/K}{\partial r_s/r_s} = (1-\delta)^s \frac{P_0 \cdot \epsilon}{K_0}$$

which implies that, the elasticity of K to r_s of s periods before is proportional to $(1-\delta)^s$.

Last, I use the approximated slope of $\log K$ to $\log r_s$ to construct the instrument:

$$Z = \sum_{s=0}^{\infty}(1-\delta)^s \log r_s$$

There is limited periods in the data, so I compute the cumulative sum up to the maximum period of each company in the analysis.

Appendix F Discussion of Instruments

F.1 Exclusion Restrictions

The exclusion restrictions require that the instrumental variable I adopt is uncorrelated with the error terms in the second stage; that is, $corr(Z, \epsilon) = 0$. As previously discussed, I will discuss the two types of endogeneity problems: simultaneity and sorting.

The simultaneity problems that threaten our identification only exist when the R&D tax credit policy in the U.S. is correlated with unobserved economic shocks in China. The introduction of R&D tax credit was in the Economic Recovery Tax Act of 1981, which is far before China accesses WTO (and the starting year of our sample period), so it is unlikely that the initiation of the R&D tax credit programs is related to any Chinese local shocks. The state specific R&D tax credit, on the other hand, was introduced and modified separately by each state in the subsequent decades, and such state level policy changes might be correlated with local shocks in China. To test that, I first compare the lagged firm-specific user cost of R&D capital between firms that mentioned China in their 10K reports between 2000 and 2007 and firms that did not. If the local shocks of China do affect R&D tax credit policy decisions in the U.S., there should be a significant difference in the R&D tax credit, and hence user costs of R&D capital, between firms that have operations in China and firms isolated from China. The comparison is shown in Figure A.2, in which I find the differences of cumulative R&D user costs to be stable over time, suggesting that the two groups of firms are unlikely to be treated differently under the R&D tax credit policies. Secondly, I match the state-level R&D tax credit changes from 2000 to 2007 with the changes of Chinese import competition from 2000 to 2007 introduced by Autor et al. (2013). If the local economic shocks in China influence the policy making process of the U.S. state government, it is likely that such shocks would channel through Chinese import shocks to the U.S.. As shown in Figure A.3, the changes of state level R&D tax credit is unlikely to be correlated with Chinese import competition shocks. Those anecdotal evidence show that, the instrumental variable I applied, i.e. the U.S. state-level R&D tax credit policies, is unlikely to be directly correlated with the unobserved economic shocks in China.

Secondly, I address the sorting problem discussed in the previous sections. The problem arises when multinationals with different innovation capacity 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* instrument changes. For the *ex-ante* firm outcomes, I select the following variables constructed directly from the ASIE data: the levels and growth of output, TFP, markups, and wage bills from 1998 to 2000. For each of those variables, I test its correlation with the change of the county level user cost of R&D capital from 2000 to 2007 (and the change of the county level spillover strength from 2000 to 2007). The test results are presented in Figure A.4. The results imply that there is only weak correlations between the changes of the local firms' outcomes before 2000 and the changes of corresponding user cost R&D capital after 2000. Furthermore, the correlations between the *ex ante* changes of the local firms' outcomes and the patent stock growth after 2000 are also insignificant, as shown in Figure A.5, implying that sorting might not be a major concern in both our IV estimates and OLS estimates.

F.2 Inclusion Restrictions

In this section I test the inclusion restrictions. Since the construction of the technology shock measures and the instrumental variables involves both weighted average/sum and non-linear transformation of taking logarithm, the underlying mechanism of the negative relationship presented in the first-stage regressions is unclear. Meanwhile, although previous literature has shown that firms' R&D investment are negatively impacted by the user cost of R&D capital, few evidence suggests that the strong negative relationship with the user costs of R&D capital would still hold for patent stocks. To address those concerns, I perform our test of inclusion restrictions in three steps. First, I regress firm's log citation-weighted patent counts[52] in each state on the 3 year-average R&D capital user cost for all years from 1976 to 2007; I also perform the test using negative binomial models and Poisson pseudo-likelihood models on citation-weighted patent counts (I use the floor of non-integers to approximate integers), as those models normally yield better fitness for count data with many 0's. Second, I test the relation at the U.S. firm level, by regressing log citation-weighted patent stocks on the firm-level cumulative user cost of R&D capital for all U.S. firms, and firms matched to subsidiaries in China, from 2000 to 2007.

The two sets of results are shown in Table A7. In panel A, I first show that the 3-year average R&D capital user cost has a strong negative impact on the number of patents at firm-state level. A 1% decrease in the log user cost will lead to about 5.5% to 6.4% increase in number of patent applications. A potential problem about using the linear regression model on the log patent application is that there are many observations with value 0 in the data. I address such concerns using the negative binomial model and the Poisson regression model, and I find the negative relation persists in these two models. In panel B, I aggregate the patent counts and user cost of R&D capital to the firm level, and find the negative relation still holds for log patent stocks and cumulative R&D user cost at the firm level for all U.S. firms, indicating that a 1% decrease in the cumulative user cost of R&D capital is associated with a 1.5% to 2.0% increase in the citation-weighted patent stocks. When I restrict our sample to only those firms matched to any Chinese subsidiaries, I find the

[52]To account for 0's, I adjust the number by adding the minimum non-zero patent counts to the original counts.

coefficient is similar in magnitude comparing to the coefficient for all U.S. firms, implying a 1% decrease in the cumulative user cost of R&D capital will increase citation-weighted patent stocks by 1.8% to 1.9%, depending on the weighting scheme.

Appendix G Discussions on TFPR and TFPQ

The revenue-based productivity measures, including TFPR and labor productivity, measures the output value produced by each unit of input (or combination of inputs). Although the measures themselves are economically meaningful, they also incorporate variations in market power across producers, as suggested in Syverson (2011) and many other studies. If more productive producers charge lower prices, the revenue-based productivity measures will be downward biased comparing to the underlying production efficiency ($tfpq$). In the baseline regressions, the cross-time industry-level variations of market power is absorbed by the industry-year fixed effect; however, the within-industry variations of market power is not addressed due to data limitations. In this section, I discuss the implications of the baseline results on the production efficiency (TFPQ) under certain model assumptions.

By definition, I write the elasticity of the revenue-based productivity (TFPR or labor productivity) in response to multinationals' technology stocks s as the following:

$$\frac{d\pi_{it}}{ds} = \frac{dp_{it}}{ds} + \frac{d\omega_{it}}{ds}$$

where π_{it} is the revenue-based productivity, p_{it} is the value-added output price, and ω_{it} is the production efficiency. In words, the response of revenue-based productivity to the technology stocks is the sum of the response of value-added output price and the response of production efficiency.

I assume that the firm production function is Cobb-Douglas with constant return to scale (CRS): $y = a + \alpha l + (1 - \alpha)k$. I further assume that wage w is given at the local level, and the interest rate r is fixed (the supply elasticity of capital is infinite and the price of capital is determined by the international market).

In the first case, I assume that each county produces a distinct variety of product, and the market for each product (in each county) is perfectly competitive, following Armingon (1969). Then $\frac{dp_{it}}{ds} = \frac{dmc_{it}}{ds} = 0$ as the production efficiency gains from local technology spillovers will be offset by the local wage increases. Therefore the effect of multinational technology stocks on TFPR equalizes the effect on TFPQ, or $\frac{d\pi_{it}}{ds} = \frac{d\omega_{it}}{ds}$. Therefore, under the Armington setting of perfect competition, the baseline results suggest that the technology shocks improve firms' production efficiency at the same scale.

In the second case, I assume monopolistic competition in each industry, so that firms in each industry face a constant markup $\frac{\sigma}{\sigma-1}$. Following Hsieh and Klenow (2009), TFPR should be equalized in each industry given input prices, and TFPQ could be written as:

$$\omega_{it} = \frac{\sigma}{\sigma - 1} q - \alpha l - (1 - \alpha)k$$

in which $q = p + y$ is the total output value, and σ is the demand elasticity. Therefore TFPQ can be recovered if the production elasticity and the demand elasticity have been estimated correctly. However, the approach will be threatened if the multinational technology spillovers also change the demand elasticity.

I first construct a measure of markup following De Loecker and Warzynski (2012). The estimated markup could be written as:

$$\hat{\mu}_{it} = \hat{\beta}_l \left(\frac{wagebill}{exp(\hat{y})}\right)^{-1}$$

In other words, the estimated markup is the ratio between the elasticity of labor input and the share of labor expenditure in total output value.

I first test whether the estimated firm-level markups are affected by the technology spillovers[53]. I further recover TFPQ based on the estimated production elasticity and demand elasticity in the following three ways: first, I assume $\sigma = 3$ for all industries; second, I assume σ to be constant within each industry group, using industry aggregated output values and wage-bills to compute labor expenditure shares; third, I assume σ to be constant within each industry-year group, using industry-year aggregated output values and wage-bills to compute labor expenditure shares. I recover firm-level TFPQ under each assumption respectively, and repeat my baseline analysis on the TFPQ measures.

My findings are summarized as following. First, the firm-level estimated markups, or

[53] See Table A11.

labor expenditure shares in total output, is not responding significantly to the technology spillovers, suggesting that the demand elasticity remains constant under monopolistic competition assumptions. Second, the technology spillovers causally increase the TFPQ measures as well, and the implied magnitudes of the point estimates are even larger than the baseline. The results imply that under monopolistic competition assumptions, the TFPR gains are likely to be associated with production efficiency improvements.

Last, the TFPR growth in response to the technology spillovers is accompanied by local wage growth. There are two hypotheses explaining why the local wages might respond positively to the multinationals' technology spillovers. First, the local labor market might be tightened following the technology spillovers. Second, the human capital stocks of the subsidiaries and the domestic firms are improved. Due to the lack of convincing unemployment and job vacancy data at county level in China from 2000 to 2007, the first hypothesis is hard to verify. Nevertheless, I find evidence consistent with the second hypothesis, as the technology spillovers causally increase the percentage of high-skilled workers (defined as workers with college degrees) in the workforce of the local areas[54], suggesting that the local human capital stocks respond positively to the technology spillovers. In other words, the productivity gains may be associated with the agglomeration spillovers of the high-skilled labors. [55].

Appendix H Conceptual Framework of Technology Adoption

H.1 Setup

I start with a generalized conceptual framework to formalize the problem. I assume a mass of M local firms with productivity expressed as:

$$\omega(i) = \omega_0(i) + \theta s$$

where $\omega_0(i)$ is firm i's initial productivity draw from a distribution $\phi(\cdot)$ of productivity levels bounded by 0 below, and s represents the external technology shocks.

[54]See Table A12.

[55]See, for example, Combes and Gobillon (2015), for a summary of the related literature.

Firms are able choose between two alternative production technologies, type H and type L. The profit function of each production technology type can be written as: $\pi(\omega; X) - f^X(s)$, where $X = H, L$. Without loss of generality, I assume that $\pi(\omega; X)$ is increasing in ω.

The setup above highlights the dual role of the technology spillover term s: on one hand, it directly improves local firms' production efficiency; on the other hand, it changes local firms' easiness of adopting production technologies. I will discuss the second role of spillovers later in detail under the applications of the conceptual framework.

I further make the following two assumptions:

Assumption 1 (Strict single-crossing condition): $\Delta\pi(\omega) \equiv \pi(\omega; H) - \pi(\omega; L)$ is strictly increasing in ω;

Assumption 2 $\Delta f(s) \equiv f^H(s) - f^L(s) > 0$ for any s.

The above two assumptions portray the difference between H and L technology types: return to productivity is higher under the H type, but the associated fixed cost is also higher.

The assumptions can directly lead to the following proposition:

Proposition 1 For any s there exists a unique $\omega^*(s)$ such that a firm chooses H if and only if its productivity is less than $\omega^*(s)$.

The proof of the proposition is straight-forward: a firm prefers H than L if and only if $\Delta\pi(\omega) \geq \Delta f(s)$. Since $\Delta\pi(\omega)$ is strictly increasing in ω, there must be a unique $\omega^*(s)$ such that $\Delta\pi(\omega^*(s)) = \Delta f(s)$, and any firms with productivity equal or above $\omega^*(s)$ will choose H (henceforth referred to as H-type firms), while any firms with productivity below $\omega^*(s)$ will choose L (henceforth referred to as L-type firms). Furthermore, the cutoff of productivity draws can be written as $\omega_0^*(s) = \omega^*(s) - s$. Therefore $\Phi(\omega_0^*(s))M$ firms will choose L-type technology, and $(1 - \Phi(\omega_0^*(s)))M$ firms will choose H-type technology.

I further discuss how the external technology shock s induces firms to switch between technology types under the following three cases.

Case 1 $\Delta f(s)$ is a constant.

Under the first case in which the gap between the fixed costs of H and L is a constant, the technology spillover term s is irrelevant for the productivity cutoff, as the productivity cutoff only needs to fulfill $\Delta\pi(\omega^*) = \Delta f$. The cutoff of productivity draws can be written as $\omega^* - s$, which is decreasing in s. Therefore a positive number of firms will switch from L to H with an increase of technology spillovers s under case 1.

Case 2 $\Delta f(s)$ is decreasing in s.

Under the second case the gap between fixed costs shrinks with technology spillover growth, or technology spillovers make it relatively easier to access the H-type technology than the L-type technology for local firms. Since $\Delta\pi(\omega)$ is increasing in ω and $\Delta f(s)$ is decreasing in s, and $\omega^*(s)$ fulfills $\Delta\pi(\omega^*(s)) = \Delta f(s)$, $\omega^*(s)$ will be decreasing in s. The cutoff of initial productivity draws is $\omega^*(s) - s$, which is also decreasing in s. Therefore a positive number of firms will switch from L to H with an increase of technology spillovers s under case 2.

Case 3 $\Delta f(s)$ is increasing in s.

Case 3 represents a more interesting case, in which the fixed cost of accessing L-type technology is relatively lower with technology spillover growth. Under case 3, the productivity cutoff is increasing in s, and the cutoff of initial productivity draws, $\omega_0^*(s) = \omega^*(s) - \theta s$, can be either increasing or decreasing in s:

$$\frac{d\omega_0^*(s)}{s} = \underbrace{\frac{d\omega^*(s)}{ds}}_{\textit{fixed cost effect}} - \underbrace{\theta}_{\textit{productivity effect}}$$

The first term, $\frac{d\omega^*(s)}{ds}$, represents a "fixed cost" effect, namely the reduction of productivity cutoff associated with technology spillovers, and the second term, $-\theta$, represents a "productivity" effect, namely the direct productivity gains from technology spillovers. On one hand, if $\frac{d\omega^*(s)}{ds} < 1$, then the fixed cost effect dominates and a positive number of firms will switch from H to L with an increase of technology spillovers s. On the other hand, if $\frac{d\omega^*(s)}{ds} \geq 1$, then the productivity effect dominates and and a positive number of firms will switch from H to L with an increase of technology spillovers s.

The general setup can be easily linked to the monopolistic competition models with firm heterogeneity, for example, the Melitz-Chaney model (Melitz (2003) and Chaney (2008)) or the Melitz-Ottaviano model (Melitz and Ottaviano (2008)). Here I present a model under monopolistic competition with constant elasticity, in which technology choices will affect the demand shifter faced by the firms. The model presents two predictions that are directly associated with the empirical tests: first, more productive firms are more likely to choose H-technology comparing to the less productive counterparts under technology spillover growth; second, more profitable firms (defined by their markups) are more likely to choose H-technology comparing to the less profitable counterparts under technology spillover growth.

H.2 Applications

Assume firm i face market demand as:

$$q(i) = Q(\frac{p(i)}{P})^{-\sigma}\xi^X$$

The production function can be written as:

$$q_i = exp(\omega_i)f(l_i, k_i)$$

where ω_i is firm i's productivity, and $f(l_i, k_i) = exp(\beta_l l_i + (1-\beta_l)k_i)$.

I further assume that $\omega_i = \omega_i^0 + \theta s$, where s is the external technology shocks, and ω_i^0 is firm i's initial productivity draw.

There are two types of technology: H and L, which determines the quality shifter ξ^X, such that $\xi^H > \xi^L$. Meanwhile, firms incur overhead cost $f_i^X(s) = f^X(s) + \epsilon_i^X$ in each period, where ϵ_i^X is idiosyncratic overhead cost shocks, and $f^H(s) > f^L(s)$ for any s. For convenience, define $\Delta\xi = \xi^H - \xi^L$, $\Delta f(s) = f^H(s) - f^L(s)$, and $\Delta\epsilon_i = \epsilon_i^H - \epsilon_i^L$.

The unit cost of production is $\frac{c(w,r)}{exp(\omega_i)}$, where $c(w,r)$ is a function of wage w and interest rate r. Profit maximizing yields the price rule as: $p_i = \frac{c(w,r)}{\rho exp(\omega_i)}$, where $\rho = \frac{\sigma-1}{\sigma}$.

Firm i's profit under technology X can be written as:

$$\pi(\omega_i, X; s) = \Psi \exp((\sigma-1)\omega_i) \cdot \xi^X - f_i^X(s)$$

where $\Psi = \frac{1}{\sigma} Q P^{\sigma} \big(\sigma \frac{c(w,r)}{\sigma - 1}\big)^{1-\sigma}$.

Firm i's choice of technology solely depends on the difference of realized profits. Specifically, firm i chooses H if and only if $\Delta\pi(\omega_i; s) \geq 0$, where

$$\Delta\pi(\omega_i; s) = \Psi \exp((\sigma - 1)\omega_i) \cdot \Delta\xi - \Delta f(s) - \Delta\epsilon_i$$

where $\Delta\epsilon_i = \epsilon_i^H - \epsilon_i^L$, with cumulative probability distribution function of $\Phi(\cdot)$.

For any firm with *ex-ante* productivity draw ω_0, the probability of the firm choosing L-technology is:

$$Pr(X = L|\omega_0; s) = \Phi\big(\Delta f(s) - \Psi \exp((\sigma - 1)\omega_i) \cdot \Delta\xi\big)$$

and

$$\begin{aligned}\frac{dPr(X = L|\omega_0; s)}{ds} =& \phi\big(\Psi \exp((\sigma - 1)\omega_i) \cdot \Delta\xi - \Delta f(s)\big) \cdot \\ & \Big(\underbrace{\Delta f'(s)}_{\textit{fixed cost effect}} - \underbrace{\Psi \Delta\xi exp((\sigma - 1)(\omega_0 + \theta s)) \cdot (\sigma - 1)\theta}_{\textit{productivity effect}} \Big)\end{aligned}$$

As shown in the equation, the probability of choosing the L-technology depends on two terms: the fixed cost effect term $\Delta f'(s)$ and the productivity effect term $\Psi exp((\sigma - 1)(\omega_0 + \theta s)) \cdot (\sigma - 1)\theta$, of which the former solely depends on s, and the latter also depends on the initial productivity draw ω_0.

Consider the case that $\Delta f'(s) > 0$, representing that the gaps between the fixed costs of adopting H-technology and L-technology is increasing in s. Then for any given s there exists a cutoff of initial productivity $\omega^*(s)$ such that $\frac{dPr(X=L|\omega_0;s)}{ds} > 0$ if any only if $\omega_0 < \omega^*(s)$. The relation above can be approximated by the following equation:

$$\begin{aligned}Pr(X = L|\omega_0; s) &\doteq \beta_0 + \beta_1 \cdot s + \beta_2 \cdot s \times \mathbb{1}(\omega_0 > \omega^*(s)) \\ &\doteq \tilde{\beta}_0 + \tilde{\beta}_1 \cdot s + \tilde{\beta}_2 \cdot s \times \omega_0\end{aligned}$$

and the model predicts that $\beta_2 < 0$ and $\tilde{\beta}_2 < 0$.

Tariff plays a similar role as productivity in the model. For simplicity, assume that there is no productivity heterogeneity and the tariff faced by industry i is τ_i. Then the profit of firm i can be expressed as:

$$\pi(\tau_i, X; s) = \Psi \tau_i^{-1} \exp((\sigma - 1)\omega) \cdot \xi^X - f_i^X(s)$$

and it is easy to show that: there exists a cutoff of tariff $\tau^*(s)$ such that $\frac{dPr(X=L|\tau;s)}{ds} > 0$ if any only if $\tau > \tau^*(s)$. Similarly, the relation can be approximated by the following equation:

$$\begin{aligned} Pr(X = L|\tau; s) &\doteq \beta_0 + \beta_1 \cdot s + \beta_2 \cdot s \times \mathbb{1}(\tau > \tau^*(s)) \\ &\doteq \tilde{\beta}_0 + \tilde{\beta}_1 \cdot s + \tilde{\beta}_2 \cdot s \times \tau_0 \end{aligned}$$

and the model predicts that $\beta_2 > 0$ and $\tilde{\beta}_2 > 0$.

Appendix I Additional Figures and Tables

Figure A.1: Example of Name Matching Procedure

This figure shows an example of the matching procedure. In the first step (not shown here), I use text scraping tools to identify U.S. public firms operating in China during years around 2000. In the second step, I manually extract the names of the subsidiaries (if exist) from both Exhibit 21 and the main text of the 10-K files. In the third step, I search for the keywords of the names in Chinese, and find the exact names of those subsidiaries. In the last step, I search for the exact names in the ASIE data. I also double check the information in the ASIE data with the information in the 10K and the online searching results to ensure the matching accuracy.

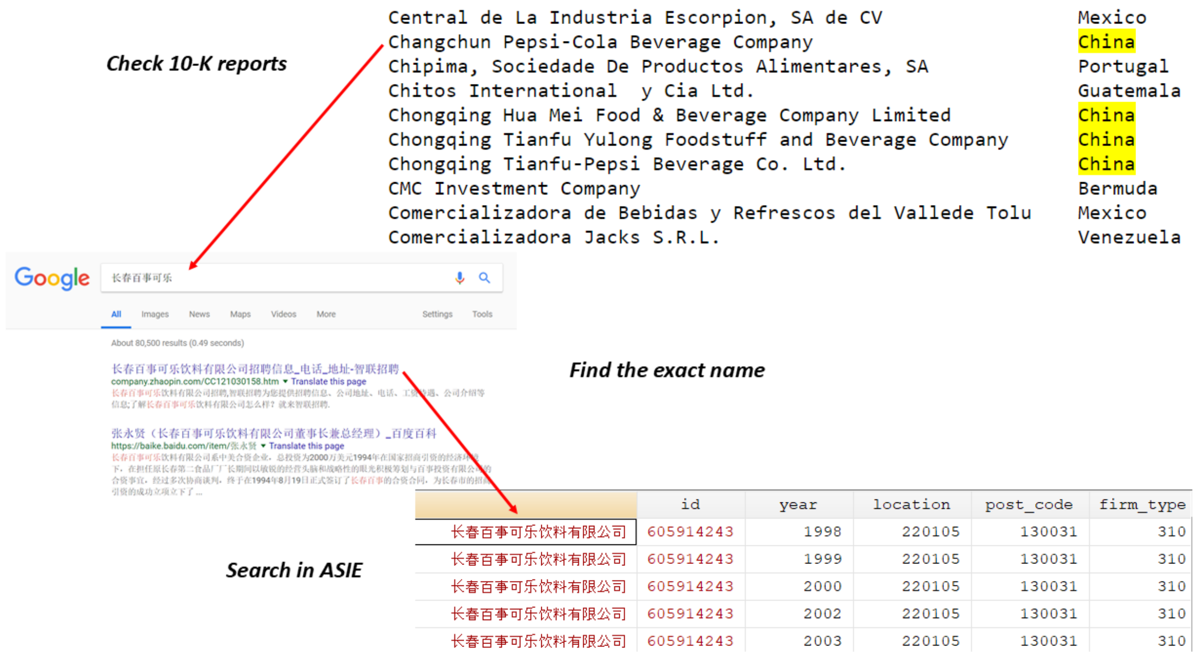


Figure A.2: Reflection: Line Plot of User Cost Comparison

The figure shows the comparison of the constructed U.S. firm-level instruments of firms operating in China and other firms. The long dashed lines show the annual average, and the dashed lines show the upper/lower 95% confidence intervals. The red lines show the change of instruments of firms operating in China, and the blue lines show the change of instruments of other firms.

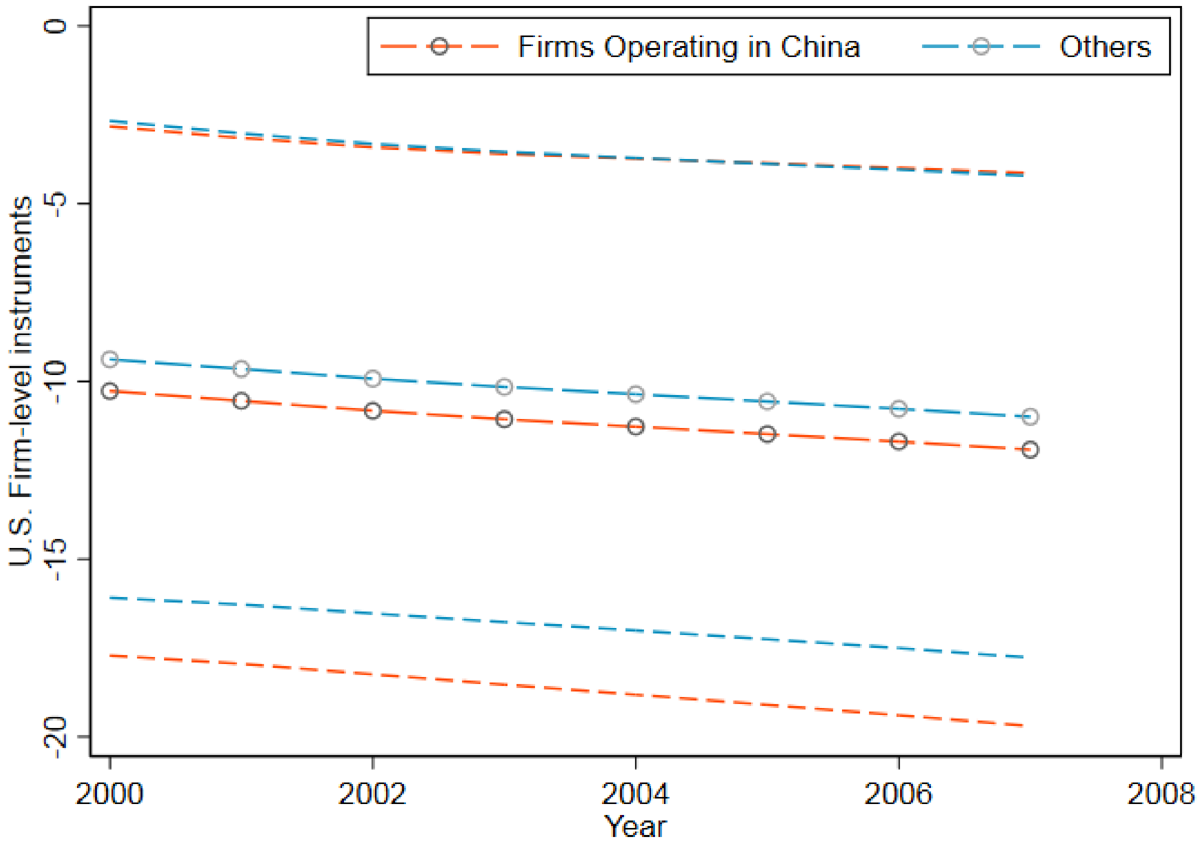


Figure A.3: Reflection: Chinese Import Competition and R&D Tax Credit (2000-2007)

The figure shows the scatter plot of state R&D tax credit changes from 2000 to 2007 versus state-level import competition changes from 2000 to 2007 based on Autor et al. (2013). The red dot line shows the OLS fit, and the blue dot line shows the IV fit, using import competition to other high-income countries as the instrument. Robust standard errors are reported.

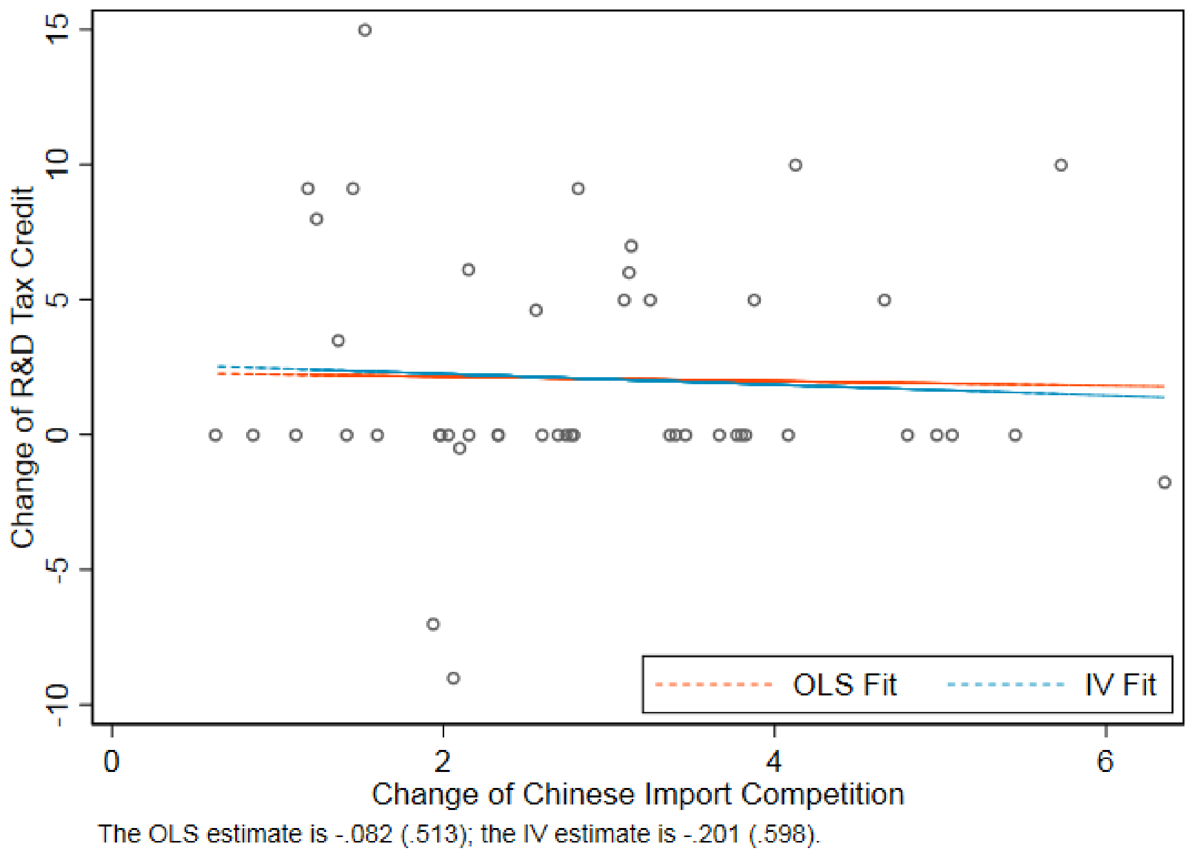


Figure A.4: Sorting: initial growth and instrument change

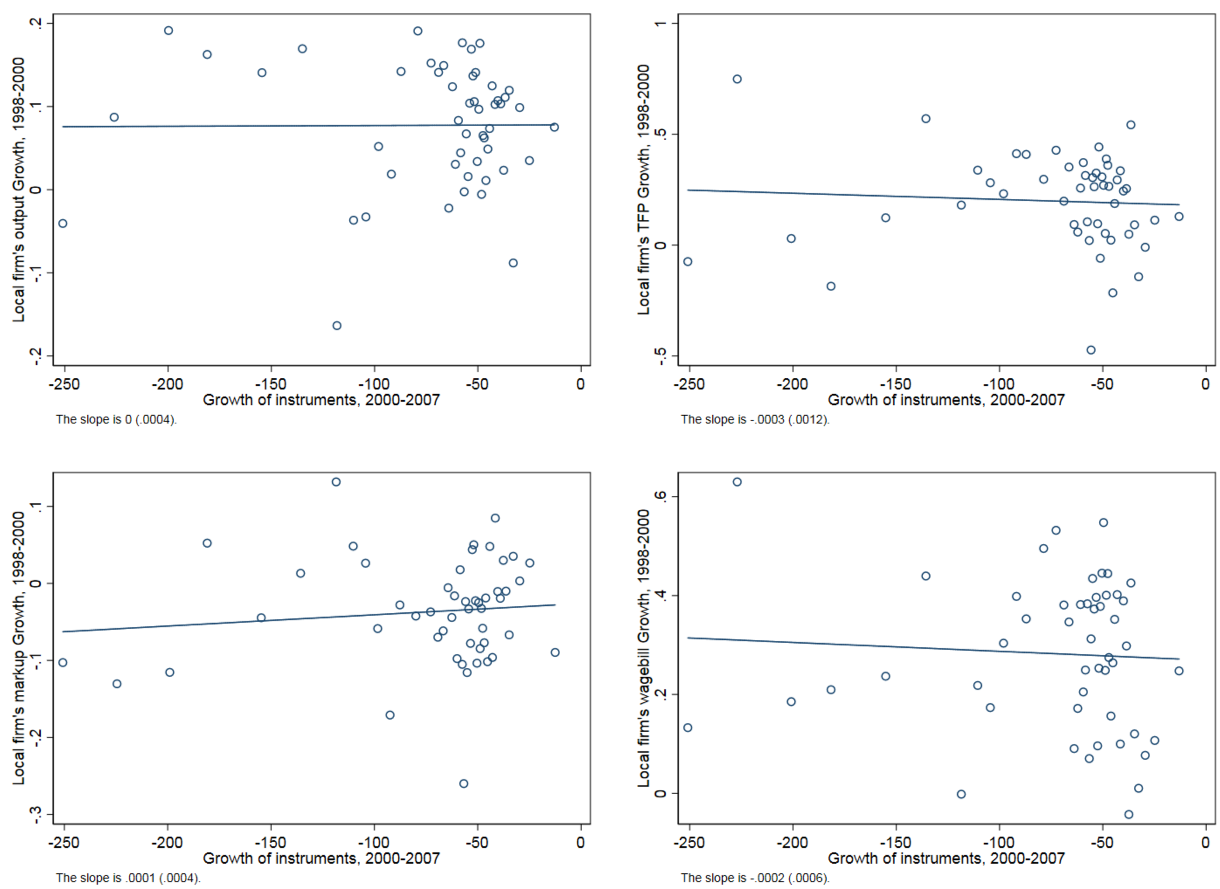


Figure A.5: Sorting: initial growth and spillover changes

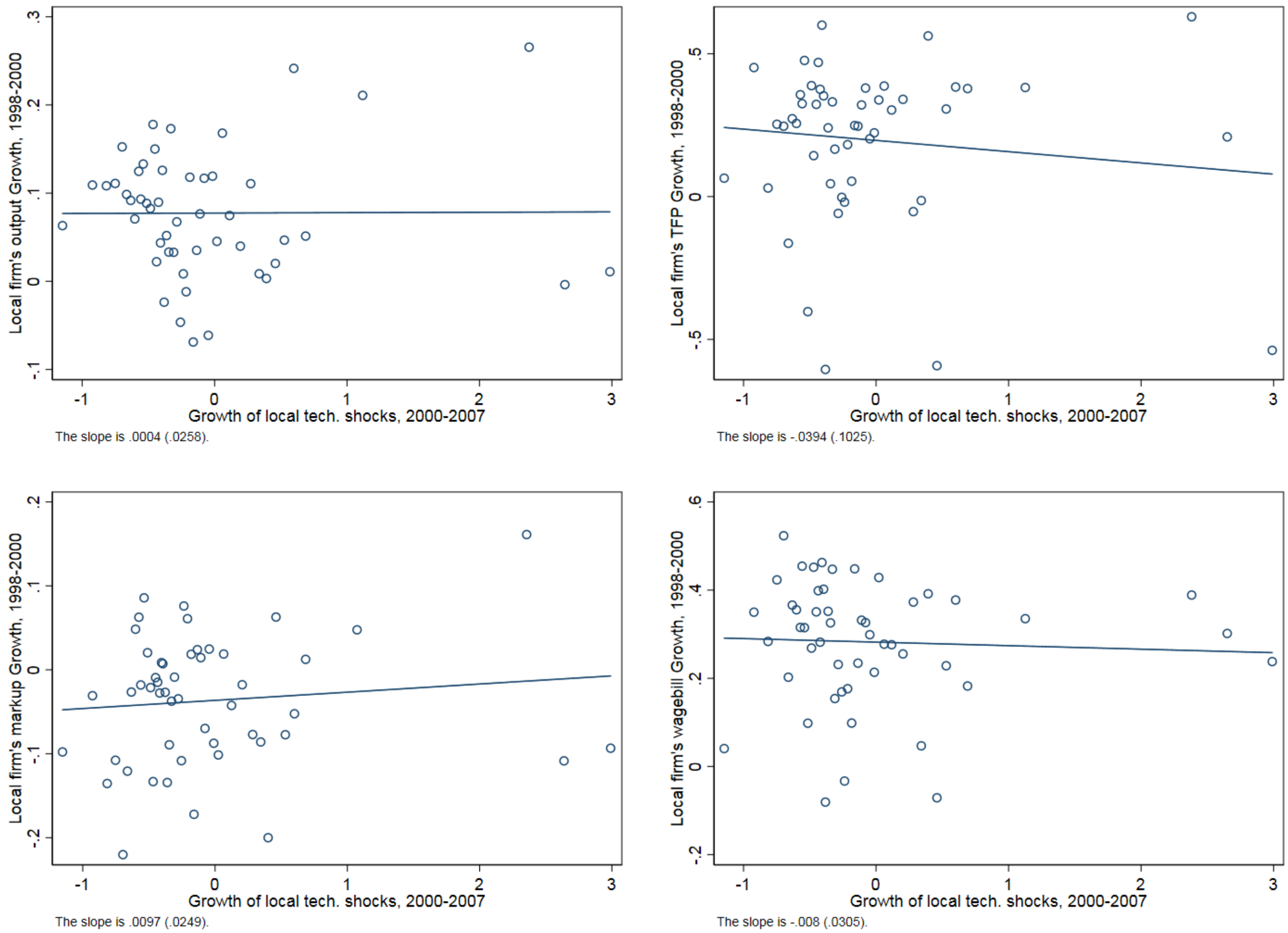
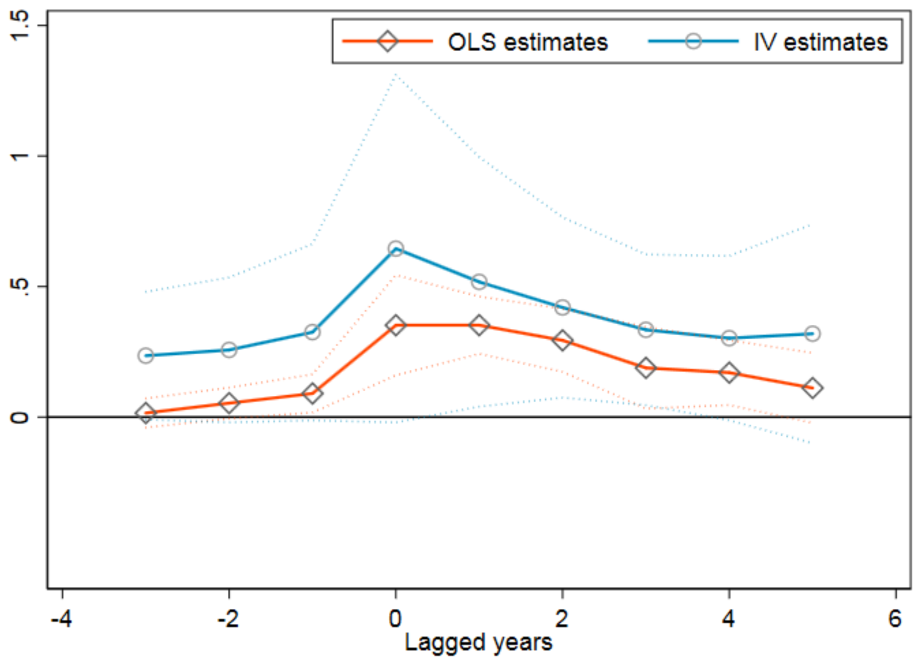


Figure A.6: The lagged effects of technology shocks

The figures show the relationship between the estimated impacts of technology shocks and lagged years. The top panel shows the relationship between parent-subsidiary technology transfer effects and lagged years, and the bottom panel shows the relationship between local technology spillover effects and lagged years. OLS and IV estimates, and the corresponding 95% confidence intervals are shown in the figures.

Parent-subsidiary technology shocks



Local technology shocks

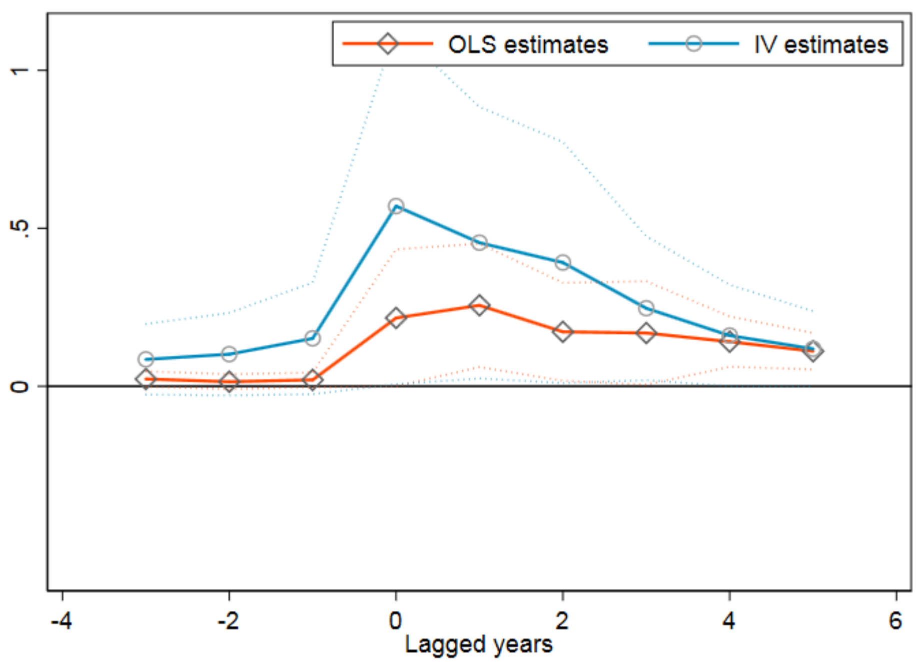


Table A1: Examples of U.S. Companies and their First Chinese Subsidiaries

Company Name	Entry Year	City
Coke Cola	1979	Beijing
Pepsi	1981	Shenzhen
Johnson & Johnson	1982	Beijing
Hewlett-Packard	1985	Beijing
P&G	1988	Guangzhou
Dupont	1988	Shenzhen
General Electric	1991	Beijing
IBM	1992	Shanghai
Motorola	1992	Tianjin
Emerson Electric	1992	Shenzhen
Colgate-Palmolive	1992	Guangzhou
Intel	1994	Shanghai
Eastman Kodak	1995	Shanghai
United Technologies	1997	Tianjin
Abbott Laboratories	1998	Shanghai
Dows Chemical	1998	Shanghai

Table A2: Source Countries/Regions of FDI in China, 2006

Country/Region	FDI Inflows (Million)	% of Total FDI
Hong Kong	17948.79	29.75
Virgin Islands	9021.67	14.96
Japan	6529.77	10.82
Republic of Korea	5168.34	8.57
United States	3061.23	5.07
Singapore	2204.32	3.65
Taiwan	2151.71	3.57
Cayman Islands	1947.54	3.23
Germany	1530.04	2.54
Samoan	1351.87	2.24
Netherlands	1043.58	1.73

Table A3: Matching Rate of Subsidiaries

	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	164	325	128,565

Table A4: Top 15 U.S. Companies in China, by 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

Table A5: Estimated production function coefficients, by 2-digit Industries

Industry code	Industry name	β_k	β_l
13	Agriculture Food Processing	0.174003	0.739058
14	Other Food Production	0.1958791	0.672882
15	Beverages	0.1674876	0.76199
16	Tobacco Products	0.2276148	0.386269
17	Textiles	0.1426196	0.633426
18	Textile Wearing Apparel, Footwear and Caps	0.1773427	0.582859
19	Leather, Fur, Feather and Related Products	0.1380673	0.613715
20	Processing of Timber, Articles of Wood, Bamboo, Rattan, Palm and Straw	0.1309988	0.744271
21	Furniture	0.2006503	0.567861
22	Paper and Paper Products	0.1401398	0.831516
23	Printing and Reproduction of Recording Media	0.25075	0.649513
24	Cultural, Educational, Arts and Crafts, Sports and Entertainment Products	0.1454942	0.552012
25	Processing of Petroleum, Coking and Nuclear Fuel	0.1895107	0.703554
26	Chemicals and Chemical Products	0.1748807	0.778609
27	Pharmaceutical Products	0.1718737	0.833414
28	Man-made Fibres	0.1650545	0.738837
29	Rubber Products	0.1434468	0.66752
30	Plactics Products	0.2050784	0.603894
31	Non-metallic Mineral Products	0.1579423	0.796469
32	Smelting and Processing of Ferrous Metals	0.1381721	0.964232
33	Smelting and Processing of Non-ferrous Metals	0.1416097	0.722879
34	Metal Products	0.1800619	0.645222
35	General-purpose Machinery	0.1695233	0.677773
36	Special-purpose Machinery	0.1716833	0.750849
37	Transport Equipment	0.1848537	0.707861
39	Electrical Machinery and Equipment	0.1868817	0.684713
40	Communication Equipment, Computer and Other Electronic Equipment	0.1688843	0.72104
41	Measuring Instruments and Machinery for Cultural Activity and Office Work	0.1675116	0.673344
42	Artwork and Other Manufacturing	0.1586298	0.532709

Table A6: An 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**

Table A7: Inclusion restrictions and first-stage regressions

Panel A. U.S. firm-state level, 1976-2010				
Dependent variables	*Log citation weighted counts*		*citation weighted counts*	
	(1a)	(2a)	(3a)	(4a)
Log user cost of R&D capital	-5.506***	-6.391***	-5.884***	-5.465***
	(0.820)	(0.989)	(0.984)	(0.959)
Firm fixed effects	No	Yes	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Models	OLS	OLS	NB	Poisson
Observations	513907	513898	513907	513907
R-squared	0.009	0.087		
Panel B. US Firm level, 1997-2004				
Dependent variable	*Log Citation weighted patent stock*			
	(1b)	(2b)	(3b)	(4b)
Cumulative log user cost of R&D capital	-3.106***	-3.026***	-2.224***	-2.366**
	(0.152)	(0.656)	(0.480)	(1.026)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Sample	All	Matched	All	Matched
Weighted by initial employment	No	No	Yes	Yes
Observations	12900	1232	12900	1232
R-squared	0.826	0.926	0.864	0.956

Notes: The table shows the inclusion restriction test results. Panel A presents regression results at U.S. firm-state level, with robust standard errors clustered at state-year level. Panel B presents regression results at U.S. firm level for all U.S. firms and matched firms only, with robust standard errors clustered at firm level. Panel C presents regression results at Chinese firm level, with robust standard errors clustered at parent company level in columns 1 and 2, and at Chinese county level in columns 3 and 4. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A8: Effects of the parent-subsidiary technology shocks (other outcomes)

Parent-subsidiary shocks, other outcomes				
Dependent variables	*wage*	*roa*	*intangible*	*export*
	(1)	(2)	(3)	(4)
$TECH^{sub}$	0.231*	0.0283*	0.00322	-0.0223
	(0.133)	(0.0164)	(0.00260)	(0.0535)
Observations	1957	1957	1957	1957
R-squared	0.586	0.652	0.652	0.867

Notes: The table presents the regression results of the effects the parent-subsidiary technology shocks on the other outcomes of the subsidiaries. IV estimates are shown in all columns. Firm fixed effects and industry-year fixed effects are controlled in all columns. Local economic conditions are controlled in all columns. Robust standard errors are clustered at the parent company level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A9: Effects of the local technology shocks (other outcomes)

Local technology shocks, other outcomes				
Dependent variables	*wage*	*roa*	*intangible*	*export*
	(1)	(2)	(3)	(4)
$TECH^{loc}$	0.228*	0.00523	0.00907*	0.0248
	(0.116)	(0.00713)	(0.00522)	(0.0213)
Observations	226097	226097	226097	226097
R-squared	0.528	0.636	0.209	0.852

Notes: The table presents the regression results of the effects the parent-subsidiary technology shocks on the other outcomes of the subsidiaries. IV estimates are shown in all columns. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A10: Dynamic effects of the local technology shocks

Local technology shocks, entry and exit				
Dependent variables	*Entry*		*Exit*	
	(1)	(2)	(3)	(4)
$TECH^{loc}$	-0.0159	-0.0163	-0.00829	-0.00106
	(0.0150)	(0.0160)	(0.00962)	(0.0101)
$TFPdeciles$	0.000000205	-0.000142	-0.00905***	-0.00633***
	(0.00105)	(0.00272)	(0.000879)	(0.00112)
$TECH^{loc} \times TFPdeciles$		0.0000524		-0.00101***
		(0.000802)		(0.000375)
Mean entry/exit	0.165		0.068	
Observations	191428	191428	191428	191428
R-squared	0.153	0.153	0.059	0.059

Notes: The tables shows the regression results of local technology shocks on the local firms' entry and exit in the data. IV coefficients are reported in all columns. County fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A11: Markups and TFPQ

Parent-subsidiary shocks, tfpq				
Dependent variables	μ	*tfpq1*	*tfpq2*	*tfpq3*
	(1)	(2)	(3)	(4)
$TECH^{sub}$	0.0405	0.646**	1.685**	1.550**
	(0.112)	(0.265)	(0.655)	(0.625)
Observations	1930	1957	1957	1957
R-squared	0.675	0.637	0.862	0.891
Local technology shocks, tfpq				
Dependent variables	μ	*tfpq1*	*tfpq2*	*tfpq3*
	(1)	(2)	(3)	(4)
$TECH^{loc}$	-0.0727	0.410**	0.949**	1.397***
	(0.0857)	(0.197)	(0.438)	(0.487)
Observations	225217	226097	226097	226097
R-squared	0.638	0.616	0.864	0.867

Notes: The tables shows the regression results of technology shocks on the subsidiaries and local firms' markups and TFPQ. IV coefficients are reported in all columns. In panel A, firm fixed effects, industry-year fixed effects, and local economic controls are controlled in all columns. In panel B, firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Column 2 assumes $\sigma = 3$; column 3 assumes industry-specific σ; column 4 assumes industry-year σ. Robust standard errors are clustered at the parent company level in panel A, and at the county level in panel B. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A12: Effect of the local technology shocks on the high-skilled labor ratio

Agglomeration of high-skilled labor				
Dependent variable	Change of high-skilled labor ratio			
	(1)	(2)	(3)	(4)
Models	OLS	IV	OLS	IV
$\Delta TECH^{loc}$	0.0255***	0.0501*	0.0155**	0.0497**
	(0.00949)	(0.0264)	(0.00775)	(0.0253)
Weighting	No	No	Yes	Yes
First-stage F		13.115		11.985
Observations	108	108	108	108
R-squared	0.032	0.002	0.019	-0.072

Notes: The tables shows the regression results of local technology shocks on the high-skilled labor ratio in the local areas. OLS results are reported in columns 1 and 3, and IV results are reported in columns 2 and 4. Columns 1 and 2 are unweighted, and columns 3 and 4 are weighted by the county-level labor force in 2000. Robust standard errors are reported. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A13: Robustness checks: R&D shocks

Panel A. Parent-subsidiary R&D shocks			
Dependent variables	*va*	*tfpr*	*lb*
	(1)	(2)	(3)
$TECH^{sub}_{R\&D}$	0.762**	0.495**	0.473**
	(0.347)	(0.227)	(0.220)
Observations	1565	1565	1565
R-squared	0.666	0.598	0.580
Panel B. Local R&D shocks			
Dependent variables	*va*	*tfpr*	*lb*
	(1)	(2)	(3)
$TECH^{loc}_{R\&D}$	0.733	0.729*	0.771*
	(0.448)	(0.417)	(0.456)
Observations	226097	226097	226097
R-squared	0.718	0.611	0.602

Notes: The table shows the effect of U.S. public firms' R&D shocks on their subsidiaries' and local firms' performance. IV results are reported in all columns. In panel A, firm fixed effects, industry-year fixed effects, and local economic controls are controlled in all columns. In panel B, firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the parent company level in panel A, and at the county level in panel B. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A14: Robustness checks: Other parent-subsidiary shocks

	Other parent-subsidiary shocks			
Dependent variables	*va*	*va*	*tfpr*	*tfpr*
	(1)	(2)	(3)	(4)
Sales shocks	0.839**		0.516	
	(0.393)		(0.382)	
Emp. shocks		0.722**		0.421
		(0.338)		(0.303)
Observations	1803	1803	1803	1803
R-squared	0.775	0.775	0.689	0.689

Notes: The table shows the effect of U.S. public firms' other shocks on their subsidiaries' performance. OLS coefficients are reported in all columns. Firm fixed effects, industry-year fixed effects, and local economic controls are controlled in all columns. Robust standard errors are clustered at the parent company level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A15: Robustness checks: Other local shocks

Other local shocks				
Dependent variables	*va*	*va*	*tfpr*	*tfpr*
	(1)	(2)	(3)	(4)
Local emp. share	-0.755***		-0.440***	
	(0.174)		(0.125)	
Local va share		-0.516***		-0.395***
		(0.177)		(0.128)
Observations	1260891	1260881	1260891	1260881
R-squared	0.735	0.735	0.649	0.649

Notes: The table shows the effect of U.S. public firms' other shocks on the local firms' performance. OLS coefficients are reported in all columns. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A16: Robustness checks: Trans-log production function

Translog production function				
Dependent variables	*va*	*tfpr*	*va*	*tfpr*
	(1)	(2)	(3)	(4)
$TECH^{sub}$	0.531***	0.322**		
	(0.181)	(0.154)		
$TECH^{loc}$			0.319*	0.275**
			(0.186)	(0.130)
Observations	1627	1627	208471	208471
R-squared	0.770	0.681	0.710	0.657

Notes: The table shows the effect of the multinationals' technology shocks on the subsidiaries and local firms' TFP and markups, estimated using trans-log production functions. IV coefficients are reported in all columns. In columns 1 and 2, firm fixed effects, industry-year fixed effects, and local economic controls are controlled in all columns. In columns 3 and 4, firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the parent company level in columns 1 and 2, and at the county level in columns 3 and 4. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A17: Robustness checks: Global effects of technology shocks

Global effects of technology shocks				
Depdent variables	*emp*	*sales*	*tfpr*	*lb*
	(1)	(2)	(3)	(4)
L3.Log patent stocks	0.0496**	0.0598**	0.189***	0.186***
	(0.0198)	(0.0296)	(0.0589)	(0.0594)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8715	8715	8715	8715
R-squared	0.977	0.944	0.749	0.808

Notes: The table shows the causal impact of U.S. public firms' parent stocks on their own outcomes. IV coefficients are reported in all columns. Firm fixed effects and year fixed effects are controlled in all columns. Robust standard errors are clustered at the U.S. company level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table A18: Robustness checks: Local technology shocks from outsourcing MNCs

Shocks from outsourcing companies				
Depdent variables	*va*	*va*	*tfpr*	*tfpr*
	(1)	(2)	(3)	(4)
Models	OLS	IV	OLS	IV
$TECH^{loc}$	0.332**	0.515	0.237*	0.415
	(0.153)	(0.417)	(0.124)	(0.318)
$LaggedOSshares$	0.666**	0.937	0.377	0.799
	(0.334)	(1.134)	(0.266)	(0.974)
$TECH^{loc} \times LaggedOSshares$	-0.128	-0.200	-0.0659	-0.180
	(0.0787)	(0.312)	(0.0675)	(0.267)
First-stage F-stats		6.312		6.312
Observations	226097	226097	226097	226097
R-squared	0.720	0.720	0.615	0.615

Notes: The table shows how outsourcing activities affects MNCs' technology shocks on local firms' value-added outputs and TFPR. Firm fixed effects, industry-year fixed effects, and ownership-year fixed effects are controlled in all columns. Robust standard errors are clustered at the county level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.