The Local Technology Spillovers of Multinational Firms

Robin Gong

Stanford University*

Job Market Paper

Abstract

This paper identifies the causal impact of U.S. multinationals' technology advances on their subsidiaries and the nearby domestic firms' productivity in China. By combining firm-level panel data from both U.S. and China, I match U.S. multinationals with their manufacturing subsidiaries in China and measure the multinationals' technology stocks based on their patenting activities. To address potential endogeneity concerns, I introduce an instrumental variable strategy based on the U.S. state level R&D tax credit policies. I find multinationals' technology improvements induce increase in the output and total factor productivity (TFP) of both their subsidiaries and domestic firms in local areas. I further find evidence of within-industry technology spillovers, and spillovers through technological linkages. The magnitude of technology spillovers hinges on local firms' absorptive capacities. Last, I show that multinationals' local technology spillovers stimulate innovation among the productive domestic firms.

Keywords: technology spillovers, patents, FDI, productivity, trade.

JEL codes: D22, D24, F23, F61, O19, O33

*Email: kgong@stanford.edu. I thank Nicholas Bloom, Pete Klenow, Kyle Bagwell, and Hongbin Li for their dedicated discussions and guidance. I also thank Caroline Hoxby, Pascaline Dupas, Isaac Sorkin, Daniel Xu, Matilde Bombardini, Heiwai Tang for their detailed suggestions and comments. I thank all seminar participants in Stanford University. Financial support from the Stanford Institute for Research in the Social Sciences Dissertation Fellowship and the Stanford Institute for Economic Policy Research Dixon and Carol Doll Graduate Fellowship is gratefully acknowledged.

1 Introduction

Foreign affiliates of multinational corporations (MNCs) accounted for 12% of global production in 2014[1]. The expansion of MNCs during the past several decades has been accompanied by a lengthy debate over the role of MNCs 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 and Helpman (1995)); multinational activities are one of the primary channels through which technology is disseminated globally (Keller (2004)). More specifically, through the sharing of technology between multinational parents and their foreign subsidiaries, technological advances in the home countries of the multinationals are transmitted to foreign countries (Markusen (2002)). Macro-level evidence (for example, Borensztein, Gregorio and Lee (1998)) also suggests that FDI contributes to the economic growth of these foreign countries. Potential gains from MNCs technology spillovers spur the adoption of 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 Rodrguez-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 the 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 their competition; vertically, it is difficult to distinguish the production efficiency improvements from positive demand shocks from supply chains.

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. Firstly, I match the 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

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

impact of the technology shocks from these parent companies on their subsidiaries based on the citation-weighted patent stocks of the parent companies. I further quantify the technology shocks of the MNCs on domestic Chinese firms in nearby geographic areas as the weighted sum of the parent-subsidiary technology shocks. To address potential endogeneity problems, I adopt an instrumental variable strategy based on the state-level research and development (R&D) tax credit policies in the United States (Wilson (2009), Bloom, Schankerman and Reenen (2013)). The primary analysis focuses on three sets of outcome variables, namely value-added output, revenue-based total factor productivity estimated following Ackerberg, Caves and Frazer (2015), and labor productivity measured in terms of value-added per worker.

This paper establishes two main results. Firstly, technological advances of U.S. multinationals are transmitted to their foreign subsidiaries, which improves the value-added outputs and productivity of these subsidiaries. Secondly, these technology improvements are further transmitted to domestic firms which are geographically close to the subsidiaries, thereby precipitating production expansions and productivity gains in these 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 that the revenue-based productivity improvements are more likely to be driven by production efficiency gains rather than price fluctuations and may be associated with improvements in local human capital stocks.

To advance our understanding of forms of the local technology spillover effect, I further investigate the impact of technology shocks through input-output linkages. I demonstrate that technology shocks yield both production expansions and productivity gains in the domestic firms within the same industry but only production expansions in the upstream and downstream domestic firms. The results suggest that the multinationals technological improvements would diffuse to the nearby domestic firms in the same industries and generate positive demand and supply shocks to the firms in the upstream and downstream industries.

I further construct measures of industry technology shocks based on the technological distance between MNCs and local industries (Hall, Jaffe and Trajtenberg (2001)) and examine two related questions based on the technological linkage-based measure. The first question concerns to what extent the technology spillover effect is contingent upon the local firms absorptive capacity. The second concerns how the technology shocks affect the local firms innovation decisions. Regarding the first question, I demonstrate that the impact of technology shocks is more substantial for firms with higher innovation capacity or human capital stocks and for private-owned enterprises. Regarding the second question, the results indicate heterogeneous responses of the local firms in their innovation activities; less productive firms become less likely to innovate, and more productive firms innovate more relative to less productive counterparts. The results are consistent with a theory which features both productivity gains and reductions in the fixed cost of imitation resulting from MNCs technology shocks.

This paper contributes to the literature on the following grounds. Firstly, it supplements prior studies concerning the relationship between multinational parents and foreign subsidiaries. The models of multinational production commonly presume that multinational parents and foreign subsidiaries share common technological inputs (for example, 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, Fisman and Foley (2006)); 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.

My results shed further light on empirical studies concerning multinationals spillover effects. Common measures of multinational activities in previous literature include industry shares of employment and output in foreign-owned firms. 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, Lu and Zhu (2017) report that foreign capital inflows exert a minimal or negative effect on the productivity of domestic firms in the same industry[2]; conversely, domestic firms in the upstream industries are likely to

[2]For developed countries, however, studies such as Haskel, Pereira and Slaughter (2007) and Keller and

benefit from foreign capital inflows, which has been suggested by studies including Javorcik (2004), Kugler (2006), Blalock and Gertler (2008), Javorcik and Spatareanu (2008), Javorcik and Spatareanu (2011), and Gorodnichenko, Svejnar and Terrell (2014). The classic approach is appealing in that it reflects the overall impact of multinational activities, but it may also embed challenges for precise interpretation and causal inference (Keller (2004)). This paper complements the previous studies through the following means. First, rather than relying upon the employment shares of FDI, I directly use the parent companies patent stocks to infer potential technological diffusion to their subsidiaries and domestic firms[3]. Second, I introduce an identification strategy which exclusively relies on the policy changes in the home countries of the multinationals[4]. The results indicate a substantial positive local spillover effect of multinationals innovation activities, and the effect also persists in the within-industry analysis.

Lastly, my analysis also relates to research described in the innovation literature. First, studies including Henderson, Jaffe and Trajtenberg (1993*a*), Peri (2005), Henderson, Jaffe and Trajtenberg (2005), Thompson (2006), Agrawal, Kapur and McHale (2008), and Murata et al. (2014) illustrate that knowledge spillovers (measured by patent citations) are substantially limited by distance[5]. The insights are incorporated into the paper by restricting my analysis on the domestic firms which are geographically near 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, Mairesse and Mohnen (2010), Hall (2011)) by connecting the innovation outcomes of

Yeaple (2009) find positive horizontal FDI effect.

[3]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.

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

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

multinationals with the productivity of the foreign subsidiaries and domestic firms.

The paper is organized as follows: Section 2 introduces my data and the construction of key variables. Section 3 outlines the main specification and introduces the identification strategy. Section 4 presents the baseline results, and section 5 lists the related robustness checks. Section 6 discusses the channels of local technology spillover effects, and extends the empirical approach to examine the impact of MNCs technology impacts on local firms innovation decisions. Section 8 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 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 several joint venture laws and foreign-capital laws that supported the institutional environment that protects the property rights of the foreign investors. The reform was reinforced after 1992, when Deng Xiaoping re-affirmed the 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 classification of industries underwent several rounds of revision after 2000. The net inflow of FDI skyrocketed in China after 2001, when China accessed the World Trade Organization (WTO); this increased from less than 50 billion in 2001 to about 250 billion in 2010. Figure 1 illustrates the growth of the U.S. FDI inflows and the major policy events in China between 1978 and 2010..

[Figure 1]

The U.S. multinationals FDI in China was initiated early during the Chinese market reform. The U.S. and the Peoples Republic of China established diplomatic relations in 1979, and in the following several years, numerous U.S. MNCs established their first subsidiaries in China, including Coca Cola (1979), Pepsi (1981), Johnson Johnson (1982), and Hewlett-Packard (1985).[6]).These early entrants often opted for a Chinese headquarters in major cities such as Beijing, Shanghai, and Guangzhou, but have more recently expanded their operations to the other cities. 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, and the total amount of FDI inflows in 2006 adds up to 3,061.23 million[7]).

Rich anecdotal evidence suggests that it is likely that foreign direct investment introduces technology spillovers to the local companies in China. For decades, the Chinese government has 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[8].Meanwhile, due to the weak enforcement of intellectual property protections, it is also possible for the domestic firms to imitate or reverse-engineer the products and technology of the multinationals. Foreign companies may also voluntarily share technology with local firms to prevent hold-ups by any single supplier (Blalock and Gertler (2008)). On the other hand, technology spillovers may 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 is based on the Annual Survey of Industrial Enterprises (ASIE). The data is collected by the Chinese National Bureau of Statistics (NBS), and the

[6]See Table A1 for examples of U.S. multinationals and their entry years
[7]See Table A2 for the major origins of FDI inflows in China
[8]See, for example, Jiang et al. (2018)

sample 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 the basic information of each company, including name, location, industry, ownership structure, and starting year, and performance variables, including gross output, value added, net income, fixed assets, intermediate inputs, and employment. Some items which are uncommon in the 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, namely 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. I further estimate a two-factor production function (Ackerberg, Caves and Frazer (2015)) with value added as production output and employment and capital as production inputs[9], to estimate the revenue-based total factor productivity (TFPR)[10]. 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 gross output, wage, return on assets, intangible assets, value of exports, etc. 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 by the SIPO between 1990 and 2015 and the Chinese 1% population census between 2000 and 2005.

In terms of U.S. data sources, I mainly relied upon patent data from the Harvard Patent Network Dataverse, which was primarily collected from the U.S. Patent and Trademark Office (USPTO). The data encompasses 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, and 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. public firms. I also use the annual Compustat data to access U.S. public firms information. The data compiles financial statement information of all U.S. public firms. To fulfill the purpose of this study, I construct

[9] Value-added outputs and employment are directly reported in the data, and I follow Brandt et al. (2017) to construct capital stocks using perpetual inventory method.
[10] the estimation procedure is outlined in later sections and in the appendix.

outcome measures of these U.S. public firms, such as log employment and sales.

2.3 Matching U.S. Public Firms to Their Chinese Subsidiaries

Recent research in both Economics and Finance fields has exhibited increasing interest in exploiting the textual data of firms' financial reports to garner the information not presented in the financial statements[11]. More specifically, 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 which utilize financial reports by extracting exact parent-subsidiary information from the 10-K files. Relative to the other potential data sources for determining the parent-subsidiary linkages in the literature, such as the within-company transaction records from confidential data of the U.S. Bureau of Economic Analysis (BEA)[12] or the *Name List of Foreign and Domestic Joint Ventures in China* from the Chinas Ministry of Commerce[13], the relationship is constructed directly in this paper 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 SEC database to construct these relationships. The 10-K files are annual financial reports of U.S. public firms required by the SEC, and they contain not only standard financial reports 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 which mentioned the related keywords in their 10-K files through text scraping. Specifically, I define the U.S. firms as related if their 10-K files contain "China" or "Chinese" plus "subsidiary", "operation", "facility", "investment", or "venture" in the same sentence. I also randomly select 50 financial reports to validate my search. The validation results

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

[12] Branstetter, Fisman and Foley (2006), Keller and Yeaple (2013), Bilir and Morales (2018).

[13] Jiang et al. (2018)

confirm that the searching algorithm targets the companies that have at least some 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. In cases 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 operations in China for these firms. 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 subsidiaries that are currently operating. I exclude from the list the subsidiaries that were initiated after 2000. I demonstrate that the ORBIS data adds merely two more U.S. public firms and five more subsidiaries to my final matches, which indicates that 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 exact names and information of the subsidiaries. For each potential match, I also investigate the name, location, industry, starting year, and ownership information to ensure that the match is correct[14].

Lastly, I restrict to the subsidiaries from between 2000 and 2007 to eliminate selection problems as the entry and exit decisions of the subsidiaries could be correlated with the U.S. parents innovation shocks. 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 existing between 2000 and 2007, about 20% are associated with China-related keywords, and I discover 310 U.S. public firms that include subsidiary information that can be matched to the ASIE data. I examine the main text of

[14]Figure A.2 shows my name matching procedure using Pepsi Co. as an example

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, it is unlikely that I 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 which existed from 2000 to 2007 yields 236 U.S. public firms and 460 subsidiaries in China. Matching with the patent data reduce the number of public firms to 210 and the number of subsidiaries to 370 because some of the U.S. public firms do not file any patents or were not matched to the patent database. Since I could not distinguish between the two, I eliminated these firms from my final match[15].

The largest MNC in the linkage in 2000 is Motorola Solutions Inc., which employ over 13,000 people total and experience 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, etc.), machinery (United Technologies, General Electric, Cummins, etc.), and chemistry (DuPont and Procter & Gamble)[16].

2.4 Identifying Affected Counties

ASIE does not provide exact address information for each firm; instead, it provides the county codes for each observation, but this presents two major problems: Firstly, the county codes change over the course of years, as new counties are added and old counties are eliminated from the list. Secondly, the county system is an administrative system; therefore, the counties geographic sizes and shapes differ substantially across the nation. I address the first problem by constructing a harmonized county code system that remains consistent over the course of years after examining historical changes in county codes. To resolve the second problem, I first compute the coordinates of the geographic centers of all counties in the Chinese county map in the Geographic Information System (GIS). I then apply a distance-based method to define the counties that were potentially affected by each subsidiary: I define a county as affected by subsidiary n if its county center is within 20km of the county center where n is

[15] Table A3 presents the matching rate for each step.
[16] Table A4 presents the top 15 U.S. MNCs in size from the final match.

located[17]. I am able to link 202 Chinese counties with at least one matched subsidiary of the U.S. multinationals using the above distance-based approach.

2.5 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.

The truncation problem presents a classic challenge with using the patent counts and citation counts (Hall, Jaffe and Trajtenberg (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, Jaffe and Trajtenberg (2001) and Hall, Jaffe and Trajtenberg (2005)'s quasi-structural approach, which estimates the empirical distribution function of the patent counts and citation counts for each of the six technology categories and adjusts the counts in late 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 this accounts for the importance of each patent.

I use parent company m's three-year lagged patent stock as a proxy for the potential

[17] I test my choice of distance in the robustness checks.

[18] The detailed adjustment procedure is outlined in the appendix

[19] See, for example, Hall, Jaffe and Trajtenberg (2005), Matray (2014), etc. An alternative choice is to use a 10% depreciation rate as in Keller (2002) and Peri (2005).

technology transfers from m to its foreign subsidiary n:

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

After constructing the linkages between local firms and the matched subsidiaries based on geographical distance, 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:

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

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 of subsidiary sizes.

The measure of local technology stocks can be rationalized through a simplified framework in which local technology diffusion is realized by the connections between workers in the multinationals and local firms. I first assume that 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 has contact with any other workers in the local firms with equal probability [20]. Assuming that the local economy is of size L, each worker in the local firms has an equal probability of $x \cdot \frac{L_n}{L}$ of having contact with the employees of n and benefit from the knowledge spillovers of size T_n. The technology spillovers which 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}, I have rewritten the formula as the local technology stock measure.

[Figure 2]

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

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, and 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 with the most innovative U.S. parent companies.

I begin with a 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. The later section constructs industry-specific measures of local technology stocks based on subsidiaries industry codes and technological relationships between the multinationals and local firms.

2.6 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). Since the construction of value-added output and labor productivity is straightforward, this section briefly introduces the construction of TFPR.

Since it is not feasible to directly measure firms production efficiency ($tfpq$) based on the ASIE data due to the lack of exact input and output price data at the firm level, I have instead estimated the revenue-based total factor productivity ($tfpr$) and discussed the effects on $tfpq$ under specific assumptions.

I mainly apply Ackerberg, Caves and Frazer (2015)'s 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 comprise the residual term, including 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 that 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 $\hat{\pi}_{it} = y_{it} - \hat{\beta}_k k_{it} - \hat{\beta}_l l_{it}$.

2.7 Summary Statistics

[TABLE 1]

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 relative to local firms in nearby geographic areas. The matched subsidiaries experience 191% greater average sales, employ 214% more people on average, and correspond with 151% higher measured TFPR. The subsidiaries also pay 201% higher wages to their employees and export 941% more than the local Chinese firms on average. The differences persist after controlling for county, industry, and ownership-fixed effects. Those dramatic differences not only validate our matches of U.S. subsidiaries but also indicate that these subsidiaries may induce sizable technology spillovers for local firms; this is because these subsidiaries are not only large in size but also experience technological advantages relative to local firms.

[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

3 Specification and Identification Strategy

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:

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

In these equations, n denotes matched subsidiaries, i denotes local Chinese firms, c denotes counties, and t denotes years. Y's are the outcome variables, and X_{ct} are the control variables. Firm fixed effects have been included to control for any time-invariant firm characteristics. Year-fixed effects are also controlled 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 is 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-subs diary technology transfer specification, and the robust standard errors are clustered at the county level in the local technology spillovers specification. Lastly, the regressions are weighted using the initial employment of the firms for the following reasons: Firstly, this controls for the heteroskedasticity in the initial firm size (Greenstone, Hornbeck and Moretti (2010)); second, the estimated coefficients of the regression results can be interpreted as "per capita" effects; third, it is 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 simalteneity 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, negative bias could be caused by CEO's limited attention[23]: if the CEO occasionally transfers attention from foreign operations to domestic research and development centers, then the increase in innovation outcomes in the U.S. will be associated with the contraction of foreign operations, which creates a negative bias in the OLS estimates. In the local technology spillover specification, 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 will precipitate 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 will 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 the OLS estimate. 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, then the bias would be negative; conversely, if multinationals prefer locations with higher levels of human capital stocks and faster market demand growth, then the bias would be positive.

To address potential endogeneity issues, I first restrict the sample of subsidiaries to those initiated between 2000 and 2007 so that their exit and entry decisions were 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; the following section elaborates upon this.

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

3.1 The U.S. R&D tax credit

The U.S. research & 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 by the federal government 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 for multiple times, and made it permanent in year 2015.

The introduction of the state R&D tax credit policies closely aligned 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%.

[Figure 3]

It is highly common for the effective state R&D tax credit rates to 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 our analysis); it displays significant variations in state-level R&D tax credit policy adjustments. Furthermore, the impact of these 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, Schankerman and Reenen (2013) in my instrumental variable construction[26].

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

3.2 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 3-year 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, 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 our patent stock construction) as:

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

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

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

on the initial size of the subsidiaries in China:

$$Z_{ct}^{loc} = \frac{\sum_{n \in N_c} Z_{m(n)t-3}^{sub} \cdot w_n^0}{\sum_{n \in N_c} w_n^0}$$

in which w_n^0 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 is represented as:

$$TECH_{ict}^{loc} = f_i + f_t + \lambda^{loc} Z_{ct-3}^{loc} + \nu_{ict}^{loc}$$

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]

Table 2 displays the first stage regressions. The results show that 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].

4 Results

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

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

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, Fisman and Foley (2006)). A parallel strand of literature has established that the productivity shocks of parent firms could be transmitted to their foreign subsidiaries (for example, Boehm, Flaaen and Pandalai-Nayar (Forthcoming), Bilir and Morales (2018)). However, whether technological improvements in the parent companies also generate productivity gains in the foreign subsidiaries has not yet been investigated.

I begin by studying how the matched subsidiaries' log value-added output, TFPR, labor productivity, and markups are affected by their parent companies' 3-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[29]. 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 discussed before, I weight each firm by their initial employment levels and cluster the robust standard errors at the parent company level.

[TABLE 3]

Table 3 presents the regression results. Column 1 suggests that a 10% increase in the parents lagged patent stocks is associated with a 2.4% 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 that a 10% increase in the parents lagged patent stocks causally increases the value-added outputs of the subsidiaries by 5.5%. In column 3 relative to column 2, the IV estimate is about double the OLS estimate, which may either be due to attenuation bias (since the standard error also becomes larger) or unobserved factors, such as CEO attention, as discussed previously. As demonstrated by

[29] Ownership-year fixed effects are not controlled as most firms in the sample are foreign-owned.

column 4, the TFPR is positively correlated with the parents technology shocks, but the OLS estimate presents negative bias (comparing with column 5). Column 5 and 6 suggest that a 10% increase in the parents lagged patent stocks causally increases the revenue-based productivity measures, including TFPR and labor productivity, by about 3.7% to 3.9% respectively.

I also investigate how the other firm-level outcomes of the subsidiaries respond to the parent companies' technology stocks[30]. I find that, subsidiaries' gross outputs, average wage, value of intermediate inputs, and intangible assets increase following their parents' technology improvements.

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 as follows: Do the local firms in China also benefit from the technological improvements of the multinationals in the local areas? This subsection addresses this question. It examines 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 have controlled for firm fixed effects, 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]

Table 4 presents the regression results. Column 1 shows that, a 10% increase in the local technology stocks is associated with a 1.1% increase in the local firms' value-added outputs, and the magnitude changes to 1.7% after controlling for industry-year and ownership-year fixed effects rather than year fixed effects in column 2. Column 3 shows that, a 10% increase in the local technology stocks causally leads to a 3.6% increase in the value-added outputs of the local firms at 10% significance level. Like before, the IV estimate is about twice as large

[30] See Table A8.

as the OLS estimate, suggesting a negative bias due to either attenuation bias, or the global shocks as previously discussed. Column 4 shows that 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 2.6% to 2.7%.

I also investigate the effect of the local technology stocks on the other outcomes of local firms[31], and find that the local firms' gross outputs, average wage, and intermediate inputs are responding positively to the local technology stocks at at least 10% significance level.

One potential concern is that since the sample in the primary analysis is an unbalanced panel of the local firms, the identified productivity gains may not reflect technology spillovers toward the incumbent firms; they may instead reflect a sorting phenomenon in which more productive firms enter the data and less productive firms exit the data. I find that local firms entry and exit decisions are unlikely the main reason for the identified productivity gains: Local firms become less likely to exit as a result of the multinationals local technology shocks, but minimal evidence suggests a sorting effect of the local technology shocks[32].

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 (0.367) will lead to a 20.1% increase in the subsidiaries' value-added outputs, a 14.3% increase in the subsidiaries' TFPR, and a 13.7% increase in the subsidiaries' labor productivity. The one standard deviation effect of the parent-subsidiary technology transfers on TFPR explains about 9.9% of the within-firm variations of TFPR in the matched subsidiaries. In terms of economic magnitudes, back-of-envelope calculation implies that the one standard deviation effect would generate about $3688 increase to the median labor productivity of the subsidiaries.

Similarly, one within-firm standard deviation in the local technology spillovers from the U.S. multinationals (0.187) leads to a 6.7% increase in the local firms' value-added outputs,

[31] See Table A9.
[32] See Table A10.

a 4.9% increase in the local firms' TFPR, and a 5.1% increase in the local firms' labor productivity. The one standard deviation effect of the local technology spillovers on TFPR explains about 4.3% of the within-firm variations of TFPR in the matched subsidiaries. In terms of economic magnitudes, back-of-envelope calculation implies that the one standard deviation effect would generate about $299 increase to the median labor productivity of the local firms. Additionally, the intra-firm effect of technology shocks is more substantial than the inter-firm one, which can be associated with the role of firm boundaries in the transfer of technology.

4.4 Discussions

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[33]. 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

[33] See Table A11.

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 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[34], 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. [35].

5 Robustness Checks

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

[34]See Table A12.

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

5.1 Choices of technology diffusion duration and distance

In the primary analysis, I have made two seemingly arbitrary choices: Firstly, I presume that the duration of international technology diffusion through multinationals is three years. Secondly, I assume that the effective local technology spillover distance is 20 kilometers. I examine alternative choices regarding the duration and distance[36]. I find my baseline results are robust to the lagged year choices of zero to four years for the parent-subsidiary technology transfer effects, and the lagged year choices of three to five years for the local technology spillover effects. I also find the results are robust to distance choices between 0 to 30 kilometers. Furthermore, I discover that the estimated local spillover effects are decaying over distance. The attenuation of local spillovers with distance aligns with the previous findings that knowledge spillovers are geographically localized (Henderson, Jaffe and Trajtenberg (1993*b*), Hall, Jaffe and Trajtenberg (2005)).

5.2 Other shocks from multinationals

I then exploit the effects of the other shocks which originated from multinationals activities. This naturally results in an examination of the impact of R&D-based spillovers. Since 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 that the effect of R&D-based technology shocks are highly similar to the effect of the patent-based technology shocks and that an increase in multinationals R&D stocks precipitates both output growth and productivity gains among the subsidiaries and the local firms[37].

I further examine the impact of multinationals sales and employment shocks on the subsidiaries. Due to the lack of valid instruments, I could only study the correlations between the shocks and subsidiaries performance. I document that subsidiaries output and productivity are positively associated with both employment growth and sales growth among their parent companies[38].

[36]The results are shown in Figure A.7 and Figure A.8.
[37]See Table A13.
[38]See Table A14.

Previous studies using employment or output share measures have find mixed evidence of multinational technology spillovers. To exhibit 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[39]. The results reveal substantial differences between the impacts of technology shocks and size shocks.

5.3 Additional robustness checks

I use alternative TFPR and markup measures estimated based on trans-log production functions, which approximates constant elasticity of substitution (CES) production functions. I find my baseline results persist under the alternative production functions[40].

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 that the overall levels of employment, sales, TFP, and labor productivity of U.S. public companies all respond positively to their lagged patent stocks at 5% significance level[41]. The finding is consistent with previous studies on the strongly positive private returns to R&D investments (Hall, Mairesse and Mohnen (2010)), implying that the growth of 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.

[39]See Table A15.
[40]See Table A16
[41]See Table A17.

However, direct technology spillovers from U.S. parent companies to the local Chinese companies remain possible. For example, this may be possible through outsourcing contracts from parent companies. Specifically, if U.S. multinationals obtain enhanced knowledge about the local companies in China from their subsidiaries and outsource production process to these local Chinese companies, then the positive local technology spillover effect identified in our baseline regression might result from the outsourcing activities directly rather than the subsidiaries. To address this concern, I interact the local technology shock measures with the share of initial employment of outsourcing MNCs[42]. The results indicate that, the technology shocks from the outsourcing U.S. companies is unlikely the driving force of the positive local technology spillover effect identified in our baseline regressions, as increasing shares of outsourcing multinationals in the local areas (insignificantly) reduce the effect of local technology spillovers[43].

6 Extensions

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 based on the relationship between the multinationals and local firms. This section extends the previous county level measure of technology shocks into two county-industry specific measures: The first encompasses technology shocks based on the industry linkages between the subsidiaries and the local firms; the second encompasses technology shocks based on the technological linkages between the multinationals and local firms. The latter is applied further to investigate the determinants of local firms absorptive capacity and technological upgrading decisions.

[42] I identify outsourcing U.S. companies based on whether their 10-K files mention outsourcing contracts in China.

[43] See Table A18.

6.1 Input-Output 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 exerted by multinationals. The analysis is inspired by the previous studies which exploit the "size" shocks of multinationals. Convention wisdom suggests that the inflow of foreign capital intensifies competition in the industry and diminishes domestic firms' productivity as their fixed costs now spread over a smaller market (Aitken and Harrison (1999)), and benefits the upstream industries either through direct technology transfer or demand shocks (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, the technology improvements may also increase multinationals requirements concerning the quality of intermediate inputs and lower their demands for the local suppliers products, thereby producing weaker backward effects relative to the size shocks. 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 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 measure of industry-level local technology spillovers as:

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

in which $\bar{K}_{cst-3} = \sum_{n \in N_{sc}} K_{m(n)t-3} \cdot \frac{w_n^0}{W_{cs}^0}$ 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 5]

Table 5 presents the baseline results. Panel A shows the estimated within-industry effects of technology spillovers. I find that, the value-added outputs, TFPR, and markups respond positively to the technology spillovers at the significance level of at least 10%. A one within-firm standard deviation increase of the within-industry technology spillovers causally increase the local firms' outputs by 8.7% and TFPR by 5.2%. Panel B shows the estimated effects of technology spillovers to the upstream industries. I find the effect on the upstream firms' value-added outputs is weakly positive, but the effects on the productivity measures are close to 0 both statistically and economically. Panel C shows the estimated effects of technology spillovers to the downstream industries. I find the effects to be positive on value-added outputs, TFPR, and labor productivity of the downstream firms, but only significant at 10% level for the value-added outputs. A one standard deviation increase of the technology spillovers leads to a 3.1% increase in the value-added outputs.

The results first indicate the existence of within-industry technology spillover effects and that they generate production expansion and productivity gains for the local firms. Since it is unlikely that local firms output prices will increase in response to the within-industry technology shocks, the TFPR improvements are more likely to be associated with production efficiency gains. Second, the results of the upstream and downstream effects suggest that the technology spillovers are likely to generate demand and supply shocks to the upstream and downstream industries, thereby increasing their value-added outputs; however, weak evidence suggests that such demand and supply shocks improve the productivity of these firms.

Related to my baseline findings, the input-output analysis indicates that the baseline result of MNCs positive local spillover effect consists of within-industry technology spillovers, but the evidence for the cross-industry technology spillovers is minimal. However, even the magnitude of the within-industry effect on TFPR is no larger than the baseline estimates, and the significance level of the estimate is only 10%, which suggests that the traditional approach of assessing the industry-level effect of multinational shocks using the subsidiaries industry classifications may be insufficient to capture the technology spillover effects of the multinationals. The next step entails introducing a new measure of industry-specific multinational technology shocks based on the technology linkages between the multinationals and local firms.

6.2 Technology Spillovers through Technological Linkages

The industry-specific local technology stocks based on the subsidiaries industry codes could suffer from shortcomings. First, many of the multinationals and their subsidiaries are conglomerates which operate across multiple industries and are embedded with diversified technology stocks; therefore, one industry classifier might undermine the potential technology shocks to firms in the related industries[44]. Second, industry classification is generally product-based rather than technology-based, and the applications of certain technology often occur across industries (Jaffe (1986)). Therefore, it may be insufficient to measure potential impacts of MNCs technology shocks by examining outcomes of firms operating under the same industry code of the subsidiaries.

To improve the traditional measure of multinational shocks based on the industry linkages between the multinational subsidiaries and the local firms, I instead exploit the technology linkages between the U.S. multinationals and local firms. As the first step, I classify the patent stocks of U.S. firms into six technological categories defined in Hall, Jaffe and Trajtenberg (2001) and Hall, Jaffe and Trajtenberg (2005): Chemical, Computers &

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

Communications, Drugs & Medical, Electrical & Electronic, and Mechanical[45]. In other words, for each U.S. company j, I denote its technology stock by a 5-dimensional vector $\vec{K}_{jt}^{P} = (K_{jt}^{P,1}, K_{jt}^{P,2}, ..., K_{jt}^{P,6})$, in which $K_{jt}^{P,\kappa}$ denotes firm j's patent stock in technological category κ. Next, using the SIPO database merged with ASIE, I classify the Chinese patents into the six technological categories as well, and compute the percentages of patent stocks in each technological category for each Chinese industries: $\vec{p}_s = (p_{s1}, p_{s2}, ..., p_{s5})$, where $p_{s\kappa}$ denotes the share of patent stocks of technological category κ in industry s. Because the SIPO data is scarce in early years, I use the patent stocks of year 2005 to compute the shares. I then compute an industry-specific local technology spillover measure based on the technology distances between MNCs and Chinese industries:

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

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

The ideal measures of technological closeness are based on more detailed technology classification systems (for example, the measure used in Jaffe (1986) or the Mahalanobis extension used in Bloom, Schankerman and Reenen (2013)), or the pairwise technology linkages based on citations between MNCs and local firms (for example, Branstetter (2006)). There are several obstacles in applying those methods under the current analysis. First, as it is straightforward to categorize the technology codes in SIPO (International Patent Classification, or IPC) into the six technological categories, the mapping between the IPC and the CPC (Cooperative Patent Classifications, the classification system adopted by USPTO), could be complicated and inaccurate, which make it unfavorable to implement the Jaffe (1986) method. Secondly, only a limited number of Chinese inventors cite U.S. patents when filing patent applications, making it implausible to use the citation-based measures of technology linkages.

I assess the impact of multinationals industry-specific technology shocks by regressing the

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

firm-level outcomes (value-added outputs and TFPR) on the newly constructed measures of technology shocks based on the technological linkages. As previously, firm-fixed effects, sector year-fixed effects, and industry year-fixed effects are controlled. 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 county and industry, robust standard errors are clustered at the county-industry level.

[TABLE 6]

Table 6 presents the results. The local technological distance-based measure causally increase the local firms' value-added outputs and TFPR: a one standard deviation increase in the technology spillovers leads to a 7.5% increase in the value-added outputs and a 5.4% increase in the TFPR (labor productivity) of the local firms that are technologically linked to the multinationals. The magnitudes of the estimated effects are a little bigger than the baseline estimates, and are significant at 5% level. Similar to the baseline results, the OLS estimates is smaller than the IV estimates, suggesting a negative bias in the OLS regressions. Furthermore, I find the positive effects persist after controlling for the county-year fixed effects, suggesting that the local technology spillovers are mostly associated with the within-county differences of technological closeness between the local firms and the multinationals.

The technological linkage-based measure of the local technology shocks encapsulates the multinationals technology spillovers on the local firms more effectively relative to the industry linkage-based measures, since it suggests stronger causal effects on the local firms outputs and TFPR and reflects the within-county variance of the spillover effects which originates from technological closeness. I further apply the measure to address the determinants of the local firms absorptive capacity and the effects of the multinationals local technology spillovers on the local firms technological upgrade decisions.

6.3 Absorptive Capacity

Previous literature on FDI spillovers asserts that 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, Redding and Van Reenen (2004) have revealed the multifaceted role of R&D investment of both stimulating innovation and enhancing technology transfer. Blalock and Gertler (2009) notes 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: shares of new products, ex-ante wage levels, and ownership types[46].

[TABLE 7]

I first 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 [47]. I define the innovative firms as those with positive sales of new products in any year during the sample period. I then estimate the effects of the technology spillovers on the innovative firms and the non-innovative firms separately. Panel A of Table 7 suggests that the estimated effects on the innovative firms are larger and more significant than their non-innovative counterparts, implying that innovation activities play a crucial role in local firms' absorption of the external technology diffusion from the multinationals.

I then investigate whether firms' human capital stocks magnify the impact of technology spillovers. Since the typical measures of human capital stocks (such as education levels) are not observed in the data, I use firms' average wage levels as a proxy for human capital stocks. Specifically, I define the high-wage (high human capital) firms as those with initial wage levels above the median level in the corresponding two-digit industry-year groups, and then estimate the technology spillover effects on the high-wage and low-wage groups separately. The regression results are shown in panel B of Table 7. I find that, both groups expand production at similar scales according to the point estimates, but the effects on TFPR is

[46] From now on, I switch to the industry technology spillovers through technology linkages as the main measure of MNCs' spillovers; many of the results are also valid using the local technology spillover measure in the baseline models.

[47] The variable is also used in Tao, Lu and Zhu (2017) to measure innovation activities.

larger and more significant for the firms with higher wage levels, suggesting that firms with higher human capital stocks might benefit more from the technology spillovers in terms of their revenue-based productivity. However, since wage is not a sufficient measure of human capital, further research is necessary to identify the role of human capital in channelling technology spillovers.

Lastly, I examine how firms with different ownership types might respond differently to the technology spillovers. Previous studies on the Chinese economy, such as Hsieh and Klenow (2009), suggest that firms' ownership structures are associated with misallocations of production inputs. Particularly, state-owned enterprises (SOEs) in China are found to be less productive but larger relative to the other ownership types, and the inefficiency might affect SOEs' response to the external technology spillovers. I examine the spillover elasticity of SOEs and non-SOEs separately in panel C of Table 7. I find that the effects are statistically significant at level of at least 10% for both SOEs and non-SOEs, but the point estimates are larger for the non-SOEs comparing to the SOEs, suggesting that the non-SOEs are more efficient in absorbing the spillovers.

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

6.4 Technology Upgrading

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. Conceptually, a positive local technology shock exerts 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 functions[48]; second, technology improvements among the multinationals might also induce local firms to imitate or specialize in

[48]Such relation is presented in, for example, De Loecker (2011).

low-end production processes[49], which diminishes their innovation inputs. The second factor can be interpreted as a reduction in the fixed costs of adopting "low-type" technologies (such as imitation or low-end production technologies)[50]. 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, then 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 exert weak but positive or even negative effects on their innovation activities; 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 between 2000 and 2007. I classify firms into decile groups based on their lagged TFP within each two-digit industry as measures of their *ex-ante* productivity level. I construct two measures of local firms' innovation outcomes: first, log stocks of all patents; second, log stock of invention and utility model patents[51]. Conceptually, the second measure includes the patents that more effectively reflect technological improvements. I regress the two innovation outcomes on the measured local technology spillovers, the lagged TFP deciles, and the interaction of the two terms:

$$K^P_{ict} = f_i + f_t + \beta_1 TECH^{loc}_{ct} + \beta_2 TFP\_decile_{it-1} + \beta_3 TECH^{loc}_{ct} \times TFP\_decile_{it-1} + \epsilon_{ict}$$

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

[TABLE 8]

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

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

[51] There are three main types of patents in China: invention patent, utility model patent, and design patent. By definition, invention patent refers to "any new technical solution relating to a product, a process or improvement"; utility model patent refers to "any new technical solution relating to the shape, the structure, or their combination, of a product"; and 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.

Table 8 displays the regression results. Firstly, columns 1 and 3 show that the overall impact of the local technology spillovers on firm-level innovation is positive but insignificant. In column 2 and 4, I interact the technology spillover measure with the ex-ante TFP decides of the local firms, and consistent with the predictions, I find that the effect of technology spillovers is increasing in the TFP deciles. Specifically, I find moving up 1 decide in the lagged TFP level will increase the estimated effect of local technology spillovers by about 0.70% to 0.74%. Furthermore, the interaction term in column 2 is significant at 10% level, while the interaction term in column 4 is significant at 5%, showing that the effect is more statistically significant for the patents with higher technology contents.

7 Concluding Remarks

Based on a unique match between U.S. public firms and their manufacturing subsidiaries in China, and a novel identification strategy, this study provides new empirical evidence on the international knowledge transfers from parent companies to their foreign subsidiaries and then to the 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. Contrary to conventional wisdom, I find the technology spillovers are more likely to be within-industry rather than cross-industry, but the traditional industry-level measures based on subsidiaries' industry codes are insufficient to capture the range of technology spillovers. 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, technology gaps, human capital stocks, and ownership structures. The multinationals technology spillovers also accelerate the innovation process of the more productive firms in the local areas.

This study suggests several directions for future research. First, the similar approach of matching U.S. multinationals with their subsidiaries in foreign countries can be applied to investigate the spillover effects in any other countries; it may be fruitful to compare the technology spillover effects between developed and developing countries. Second, it is uncertain whether the technology diffusion from the multinationals to the local firms harms the multinationals themselves. As many of the debates concerning the current trade war between the U.S. and China have focused on the "technology stealing" of Chinese firms, it will be necessary to evaluate the consequences of multinational technology spillovers for the U.S. firms themselves. Third, the impact of the technology shocks highlighted in this study appears to differ from the impacts of employment and output shocks in the previous literature. Therefore, it will be helpful to compare and discuss how and why these shocks differ in detail. 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, 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.

References

Abebe, Girum, Margaret S. McMillan, and Michel Serafinelli. 2018. "Foreign Direct Investment and Knowledge Diffusion in Poor Locations: Evidence from Ethiopia." *NBER working paper.*

Ackerberg, Daniel, Kevin Caves, and Garth Frazer. 2015. "Identification Properties of Recent Production Function Estimators." *Econometrica.*

Agrawal, Ajay, Devesh Kapur, and John McHale. 2008. "How do spatial and social proximity influence knowledge flows? Evidence from patent data." *Journal of Urban Economics.*

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

Antras, Pol, and Stephen R. Yeaple. 2014. "Multinational Firms and the Structure of International Trade." *Handbook of International Economics.*

Arkolakis, Costas, Natalia Ramondo, Andrs Rodrguez-Clare, and Stephen Yeaple. 2018. "Innovation and Production in the Global Economy." *American Economic Review.*

Armingon, Paul S. 1969. "A Theory of Demand for Products Distinguished by Place of Production." *Staff Papers.*

Autor, David, David Dorn, and Gordon Hanson. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review.*

Bilir, Kamran, and Eduardo Morales. 2018. "Innovation in the Global Firm." *Working paper.*

Blalock, Garrick, and Paul Gertler. 2008. "Welfare Gains from Foreign Direct Investment through Technology Transfer to Local Suppliers." *Journal of International Economics.*

Blalock, Garrick, and Paul Gertler. 2009. "How Firm Capabilities Affect Who Benefits from Foreign Technology." *Journal of Development Economics.*

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

Bodnaruk, Andriy, Tim Loughran, and Bill McDonald. 2015. "Using 10-K Text to Gauge Financial Constraints." *Journal of Financial and Quantitative Analysis.*

Boehm, Christoph E., Aaron Flaaen, and Nitya Pandalai-Nayar. Forthcoming. "Input Linkages and the Transmission of Shocks: Firm-Level Evidence from the 2011 Tohoku Earthquake." *Review of Economics and Statistics.*

Borensztein, Eduardo, Jose De Gregorio, and Jong-Wha Lee. 1998. "How does foreign direct investment affect economic growth?" *Journal of international Economics.*

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

Branstetter, Lee. 2006. "Is Foreign Direct Investment a Channel of Knowledge Spillovers? Evidence from Japan's FDI in the United States." *Journal of International economics.*

Branstetter, Lee G., Raymond Fisman, and Fritz Foley. 2006. "Do Stronger Intellectual Property Rights Increase International Technology Transfer? Empirical Evidence from U. S. Firm-Level Panel Data." *The Quarterly Journal of Economics.*

Bruno, Michael. 1978. "Duality, Intermediate Inputs and Value-Added." *Production Economics: A Dual Approach to Theory and Applications.*

Bwalya, Samuel. 2006. "Foreign Direct Investment and Technology Spillovers: Evidence from Panel Data Analysis of Manufacturing Firms in Zambia." *Journal of Development Economics.*

Chaney, Thomas. 2008. "Distorted Gravity: The Intensive and Extensive Margins of International Trade." *American Economic Review.*

Coe, David T., and Elhanan Helpman. 1995. "International R&D spillovers." *European Economic Review.*

Cohen, Wesley M., and Daniel A. Levinthal. 1990. "Absorptive Capacity: A New Perspective on Learning and Innovation." *Administrative Science Quarterly.*

Combes, Pierre-Philippe, and Laurent Gobillon. 2015. "The Empirics of Agglomeration Economies." *Handbook of Regional and Urban Economics.*

De Loecker, Jan. 2011. "Product Differentiation, Multiproduct Firms, and Estimating the Impact of Trade Liberalization on Productivity." *Econometrica.*

De Loecker, Jan, and Frederic Warzynski. 2012. "Markups and Firm-Level Export Status." *American Economic Review.*

Diewert, Walter. 1978. "Superlative Index Numbers and Consistency in Aggregation." *Econometrica.*

Djankov, Simeon, and Bernard Hoekman. 2000. "Foreign Investment and Productivity Growth in Czech Enterprises." *The World Bank Economic Review.*

Gorodnichenko, Yuriy, Jan Svejnar, and Katherine Terrell. 2014. "When does FDI Have Positive Spillovers? Evidence from 17 Transition Market Economies." *Journal of Comparative Economics.*

Greenstone, Michael, Richard Hornbeck, and Enrico Moretti. 2010. "Identifying Agglomeration Spillovers: Evidence from Winners and Losers of Large Plant Openings." *Journal of Political Economy.*

Griffith, Rachel, Stephen Redding, and John Van Reenen. 2004. "Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries." *Review of Economics and Statistics.*

Griliches, Zvi. 1992. "The Search for R&D Spillovers." *The Scandinavian Journal of Economics.*

Haddad, Mona, and Ann Harrison. 1993. "Are There Positive Spillovers from Direct Foreign Investment?: Evidence from Panel Data for Morocco." *Journal of Development Economics.*

Hall, Bronwyn H. 1992. "R&D Tax Policy During the 1980s: Success or Failure?" *Tax Policy and the Economy.*

Hall, Bronwyn H. 2011. "Innovation and Productivity." *NBER Working Paper.*

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2001. "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." *NBER Working Paper.*

Hall, Bronwyn H., Adam B. Jaffe, and Manuel Trajtenberg. 2005. "Market Value and Patent Citations: A First Look." *RAND Journal of Economics.*

Hall, Bronwyn H., Jacques Mairesse, and Pierre Mohnen. 2010. "Measuring the Returns to R&D." *Handbook of the Economics of Innovation.*

Hall, Robert E., and Dale W. Jorgenson. 1967. "Tax Policy and Investment Behavior." *The American Economic Review.*

Harrison, Ann, and Anrs Rodrguez-Clare. 2010. "Trade, Foreign Investment, and Industrial Policy for Developing Countries." *Handbook of Development Economics.*

Haskel, Jonathan, Sonia Pereira, and Matthew Slaughter. 2007. "Does Inward Foreign Direct Investment Boost the Productivity of Domestic Firms?" *The Review of Economics and Statistics.*

Helpman, Elhanan. 1984. "A Simple Theory of International Trade with Multinational Corporations." *The Journal of Political Economy.*

Helpman, Elhanan. 2006. "Trade, FDI, and the Organization of Firms." *Journal of Economic Literature.*

Henderson, Rebecca, Adam Jaffe, and Manuel Trajtenberg. 1993*a*. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *The Quarterly Journal of Economics*.

Henderson, Rebecca, Adam Jaffe, and Manuel Trajtenberg. 1993*b*. "Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations." *Quarterly Journal of Economics*.

Henderson, Rebecca, Adam Jaffe, and Manuel Trajtenberg. 2005. "Patent Citations and the Geography of Knowledge Spillovers: A Re-AssessmentComment." *American Economic Review*.

Hoberg, Gerard, and Gordon M. Phillips. 2010. "Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis." *Review of Financial Studies*.

Hoberg, Gerard, and Gordon M. Phillips. 2016. "Text-Based Network Industries and Endogenous Product Differentiation." *Journal of Political Economy*.

Hoberg, Gerard, and Katie Moon. 2017. "Offshore activities and financial vs operational hedging." *Journal of Financial Economics*.

Hoberg, Gerard, and S. Katie Moon. Forthcoming. "The Oshoring Return Premium." *Management Science*.

Hsieh, Chang-Tai, and Peter J. Klenow. 2009. "Misallocation and Manufacturing TFP in China and India." *The Quarterly Journal of Economics*.

Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits and Market Value." *American Economic Review*.

Javorcik, Beata. 2004. "Does Foreign Direct Investment Increase the Productivity of Domestic Firms? In Search of Spillovers through Backward Linkages." *American Economic Review*.

Javorcik, Beata, and Mariana Spatareanu. 2008. "To Share or not to Share: Does Local Participation Matter for Spillovers from Foreign Direct Investment?" *Journal of Development Economics.*

Javorcik, Beata, and Mariana Spatareanu. 2011. "Does It Matter Where You Come From? Vertical Spillovers from Foreign Direct Investment and the Origin of Investors." *Journal of Development Economics.*

Jiang, Kun, Wolfgang Keller, Larry D. Qiu, and William Ridley. 2018. "International Joint Ventures and Internal vs. External Technology Transfer: Evidence from China." *NBER Working Paper.*

Jones, Charles I., and John C. Williams. 1998. "Measuring the Social Rate of Return to R&D." *Quarterly Journal of Economics.*

Keller, Wolfgang. 2002. "Geographic Localization of International Technology Diffusion." *The American Economic Review.*

Keller, Wolfgang. 2004. "International Technology Diffusion." *Journal of Economic Literature.*

Keller, Wolfgang, and Stephen Yeaple. 2009. "Multinational Enterprises, International Trade, and Productivity Growth: Firm-level Evidence from the United States." *The Review of Economics and Statistics.*

Keller, Wolfgang, and Stephen Yeaple. 2013. "The Gravity of Knowledge." *American Economic Review.*

Kogan, Leonid, Dimitris Papanikolaou, Amit Seru, and Noah Stoffman. 2017. "Technological Innovation, Resource Allocation, and Growth." *The Quarterly Journal of Economics.*

Konings, Jozef. 2001. "The Effects of Foreign Direct Investment on Domestic Firms." *Economics of Transition.*

Kugler, Maurice. 2006. "Spillovers from Foreign Direct Investment: Within or between Industries?" *Journal of Development Economics.*

Levinsohn, James, and Amil Petrin. 2003. "Estimating Production Functions Using Inputs to Control for Unobservables." *The Review of Economic Studies.*

Loughran, Tim, and Bill McDonald. 2011. "When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks." *Journal of Finance.*

Manski, Charles. 1993. "Identification of Endogenous Social Effects: The Reflection Problem." *The Review of Economic Studies.*

Markusen, James R. 1995. "The Boundaries of Multinational Enterprises and the Theory of International Trade." *Journal of Economic Perspectives.*

Markusen, James R. 2002. "Multinational Firms and the Theory of International Trade." *The MIT Press.*

Matray, Adrien. 2014. "The Local Innovation Spillovers of Listed Firms." *Working paper.*

Melitz, Marc J. 2003. "The Impact of Trade on IntraIndustry Reallocations and Aggregate Industry Productivity." *Econometrica.*

Melitz, Marc J., and Gianmarco I. P. Ottaviano. 2008. "Market Size, Trade, and Productivity." *The Review of Economic Studies.*

Murata, Yasusada, Ryo Nakajima, Ryosuke Okamoto, and Ryuichi Tamura. 2014. "Localized Knowledge Spillovers and Patent Citations: A Distance-based Approach." *Review of Economics and Statistics.*

Pavcnik, Nina. 2002. "Trade Liberalization, Exit, and Productivity Improvements: Evidence from Chilean Plants." *The Review of Economic Studies.*

Peri, Giovanni. 2005. "Determinants of Knowledge Flows and Their Effect on Innovation." *Review of Economics and Statistics.*

Poole, Jennifer. 2013. "Knowledge Transfers from Multinational to Domestic Firms: Evidence from Worker Mobility." *Review of Economics and Statistics.*

Romer, Paul. 1993. "Idea Gaps and Object Gaps in Economic Development." *Journal of Monetary Economics.*

Schmookler, Jacob. 1966. "Invention and Economic Growth." *Harvard University Press, Cambridge.*

Schoar, Antoinette. 2002. "Effects of Corporate Diversification on Productivity." *Journal of Finance.*

Seru, Amit. 2014. "Firm boundaries matter: Evidence from conglomerates and R&D activity." *Journal of Financial Economics.*

Stock, James H., and Motohiro Yogo. 2002. "Testing for Weak Instruments in Linear IV Regression." *NBER Working Paper.*

Syverson, Chad. 2011. "What Determines Productivity?" *Journal of Economic Literature.*

Tao, Zhigang, Yi Lu, and Lianming Zhu. 2017. "Identifying FDI Spillovers." *Journal of International Economics.*

Thompson, Peter. 2006. "Patent Citations and the Geography of Knowledge Spillovers: Evidence from Inventor and Examiner-added Citations." *The Review of Economics and Statistics.*

Wilson, Daniel. 2009. "Beggar Thy Neighbor? The In-state, Out-of-state, and Aggregate Effects of R&D Tax Credits." *The Review of Economics and Statistics.*

Figure 1: Institutional Background

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.

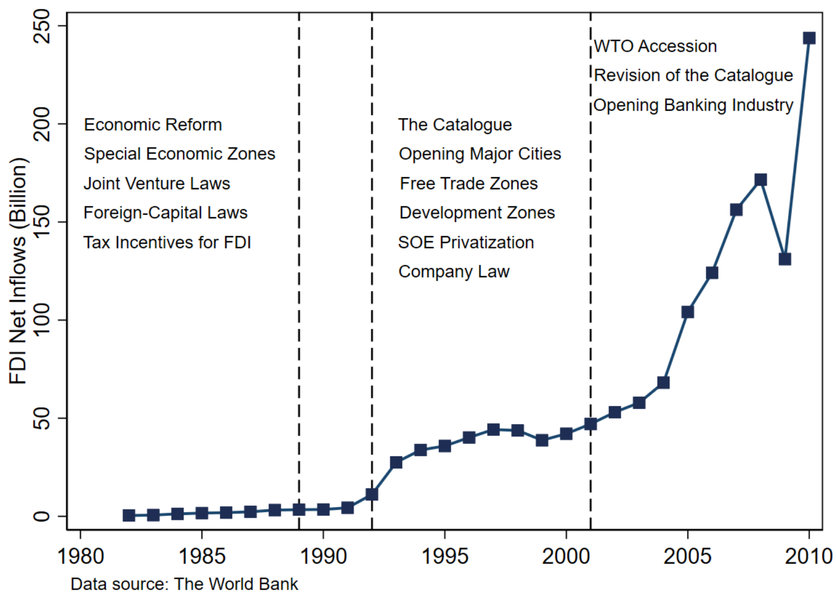


Figure 2: Geographic distribution of $TECH^{loc}$ in 2000

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 202 counties out of 2280 in total.

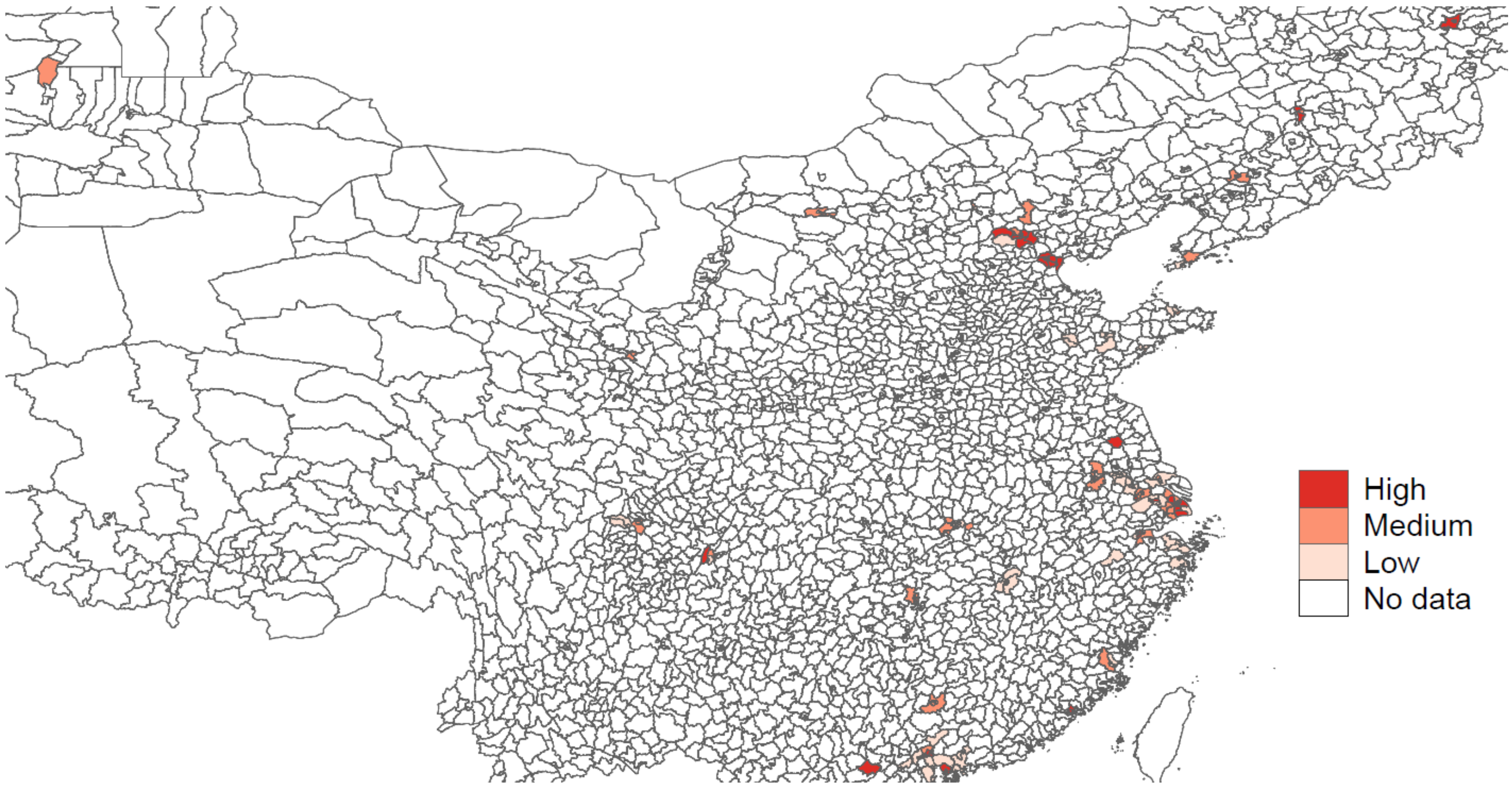
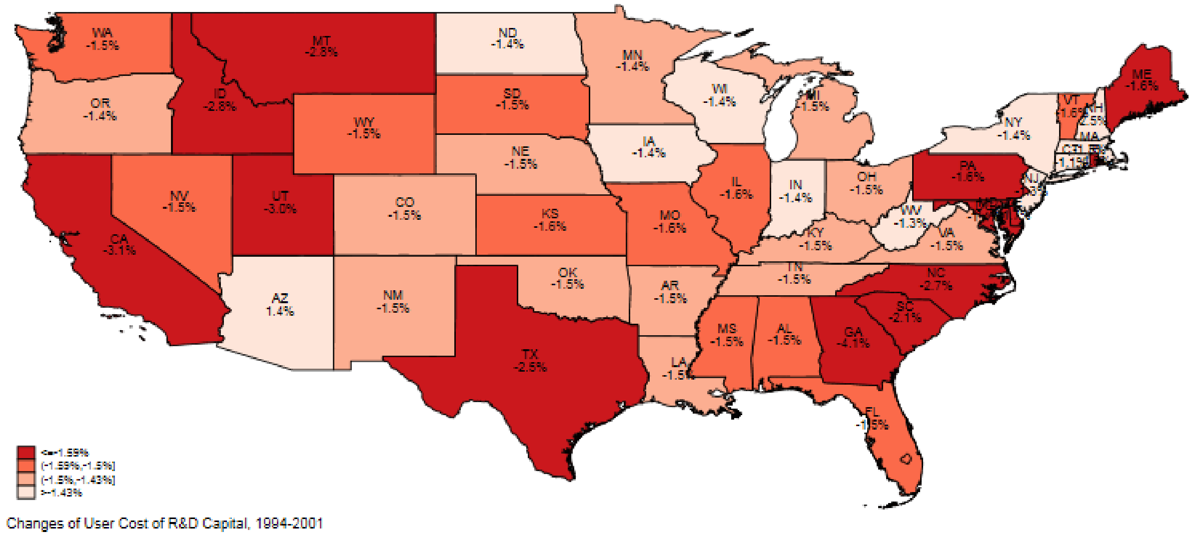


Figure 3: Changes of R&D Capital User Cost and Median Log Patent Stock

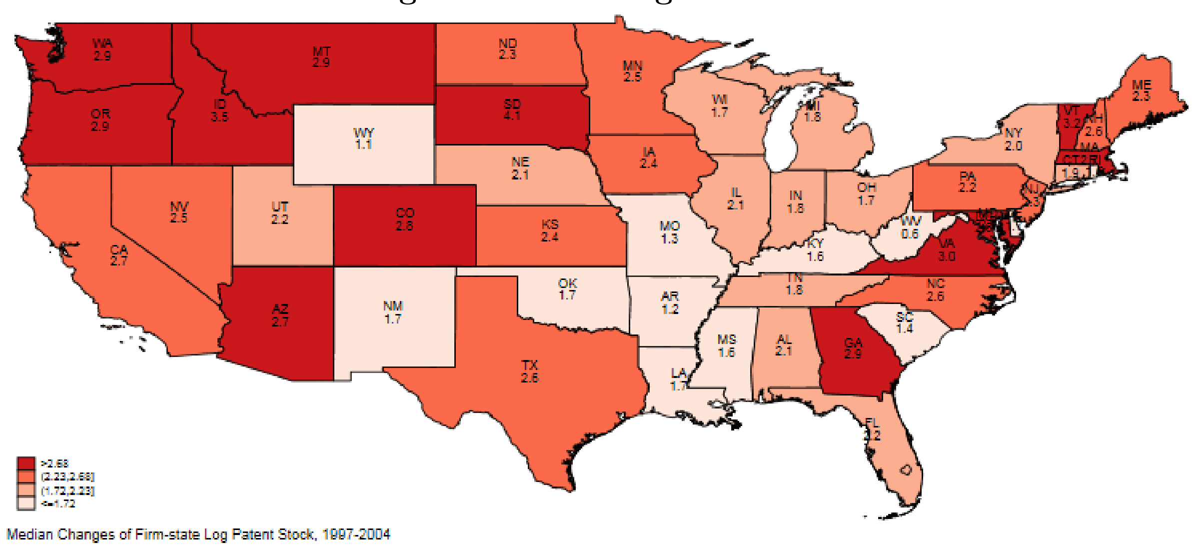
The figures show the geographic distribution of the changes of R&D capital user cost and median log patent stock. The upper figure shows the change of R&D capital user cost from 1994 to 2001, and the lower figure shows the change of median firm-state log patent stock from 1997 to 2004, corresponding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

Change of R&D Capital User Cost



Changes of User Cost of R&D Capital, 1994-2001

Change of Median Log Patent Stock



Median Changes of Firm-state Log Patent Stock, 1997-2004

Table 1: Summary statistics

Variables	**Mean**	**Median**	**Std. Dev.**	**N**
Panel A. Matched subsidiaries				
Value added (millions RMB)	193.93	52.77	1147.75	1565
Gross output (millions RMB)	677.49	188.75	4063.93	1565
TFP	3.13	3.45	1.93	1565
Markups	0.87	0.79	0.86	1565
Employment	565.74	223.00	1240.26	1565
Wage (thousands RMB)	51.13	38.96	125.70	1565
Export value (millions RMB)	301.83	24.06	2354.92	1565
Panel B. Local firms				
Value added (millions RMB)	24.55	5.01	236.70	449,028
Gross output (millions RMB)	99.45	20.51	923.32	449,028
TFP	1.89	2.06	1.68	449,028
Markups	0.71	0.64	0.79	449,028
Employment	266.41	106.00	926.13	449,028
Wage (thousands RMB)	15.87	12.87	15.24	449,028
Export value (millions RMB)	33.06	0.00	552.21	449,028
State/Collective ownership (%)	25.52			449,028
Private ownership (%)	37.96			449,028
Foreign ownership (%)	36.52			449,028
Panel C. spillover measures				
$TECH^{sub}$	7.83	8.37	2.64	1565
$TECH^{loc}$	3.84	4.29	3.38	449,028
$TECH^{within}$	3.38	3.71	3.65	65,701
$TECH^{upstream}$	0.37	0.28	4.31	315,106
$TECH^{downstream}$	0.47	0.79	3.86	318,809
$TECH^{sim}$	1.97	2.25	3.49	371,041

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.

Table 2: First-stage Regressions

First-stage regressions, 2000-2007				
Dependent variables	$TECH^{sub}$		$TECH^{loc}$	
	(1)	(2)	(3)	(4)
Z^{sub}	-1.210***	-1.202***		
	(0.348)	(0.347)		
Z^{loc}			-0.363***	-0.358***
			(0.120)	(0.113)
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	1565	1565	371041	371041
R-squared	0.991	0.991	0.997	0.997

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 level in columns 1 and 2, and at county level in columns 3 and 4. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

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
$TECH^{sub}$	0.241***	0.259***	0.548**	0.224***	0.387***	0.374***
	(0.0614)	(0.0631)	(0.217)	(0.0364)	(0.136)	(0.138)
Local controls	No	Yes	Yes	Yes	Yes	Yes
Industry-year FE	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F-stats			11.714		11.714	11.714
Observations	1565	1565	1565	1565	1565	1565
R-squared	0.693	0.693	0.691	0.623	0.633	0.601

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.

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
$TECH^{loc}$	0.113*	0.167***	0.360*	0.159***	0.263**	0.272***
	(0.0639)	(0.0534)	(0.183)	(0.0355)	(0.110)	(0.103)
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			10.356		10.356	10.356
Observations	371041	371041	371041	371041	371041	371041
R-squared	0.676	0.683	0.683	0.575	0.575	0.562

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 5: Technology shocks through input-output linkages

Panel A. Within-industry technology shocks			
Dependent variables	*va*	*tfpr*	*lb*
	(1a)	(2a)	(3a)
$TECH^{within}$	0.389**	0.233*	0.208
	(0.180)	(0.130)	(0.128)
Observations	56522	56522	56522
R-squared	0.632	0.566	0.556
Panel B. Technology shocks to upstream			
Dependent variables	*va*	*tfpr*	*lb*
	(1b)	(2b)	(3b)
$TECH^{upstream}$	0.0959	-0.00399	-0.00206
	(0.0726)	(0.0629)	(0.0631)
Observations	315294	315294	315294
R-squared	0.688	0.579	0.573
Panel C. Technology shocks to downstream			
Dependent variables	*va*	*tfpr*	*lb*
	(1c)	(2c)	(3c)
$TECH^{downstream}$	0.110*	0.0604	0.0590
	(0.0597)	(0.0541)	(0.0553)
Observations	319938	319938	319938
R-squared	0.691	0.588	0.577

Notes: The tables shows the effects of local technology shocks on the local firms' performance through industry linkages. Panel A reports the withinin-industry estimated effects, Panel B reports the estimated effects on the upstream industries, and panel C reports estimated effects on 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 at the county-industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 6: Technology shocks through technological linkages

Local spillovers through technological linkages						
Dependent variables	*va*	*va*	*va*	*tfpr*	*tfpr*	*tfpr*
	(1)	(2)	(3)	(4)	(5)	(6)
Models	OLS	IV	IV	OLS	IV	IV
$TECH^{dist}$	0.120**	0.261**	0.258**	0.0807*	0.186**	0.202*
	(0.0556)	(0.107)	(0.122)	(0.0480)	(0.0890)	(0.105)
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	No	Yes	No	No	Yes
First-stage F-stats		45.779	31.068		45.779	31.068
Observations	371036	371036	371036	371036	371036	371036
R-squared	0.683	0.683	0.711	0.575	0.575	0.606

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

Table 7: Determinants of absorptive capacity

Panel A. Innovation activities				
Dependent variables	*va*	*tfpr*	*va*	*tfpr*
	(1a)	(2a)	(3a)	(4a)
Groups	Non-innovative		Innovative	
$TECH^{dist}$	0.117*	0.0670	0.583***	0.442***
	(0.0635)	(0.0516)	(0.176)	(0.151)
Observations	313419	313419	57622	57622
R-squared	0.658	0.591	0.647	0.553
Panel B. human capital stocks				
Dependent variables	*va*	*tfpr*	*va*	*tfpr*
	(1c)	(2c)	(3c)	(4c)
Groups	Low wage		High wage	
$TECH^{dist}$	0.226*	0.142	0.278**	0.236**
	(0.130)	(0.109)	(0.137)	(0.0994)
Observations	187119	187119	183922	183922
R-squared	0.605	0.579	0.708	0.533
Panel C. Ownership types				
Dependent variables	*va*	*tfpr*	*va*	*tfpr*
	(1c)	(2c)	(3c)	(4c)
Groups	SOEs		Non-SOEs	
$TECH^{dist}$	0.227**	0.131*	0.334**	0.262**
	(0.0944)	(0.0714)	(0.156)	(0.131)
Observations	107619	107619	263421	263421
R-squared	0.697	0.605	0.662	0.531

Notes: The table shows the determinants of local firms' absorptive capacity. 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 at the county-industry level. ***, **, and * indicate significance at the 1%, 5%, and 10% level.

Table 8: Effects of technology shocks on innovation

Technology shocks and innovation activities				
Dependent variables: Log patent stocks	*All*		*Invention + utility*	
	(1)	(2)	(3)	(4)
$TECH^{dist}$	0.104	0.0784	0.137	0.109
	(0.221)	(0.225)	(0.209)	(0.214)
Lagged TFP (decile)		0.00261		0.00320
		(0.00894)		(0.00847)
$TECH^{dist}$ X Lagged TFP (decile)		0.00696*		0.00743**
		(0.00367)		(0.00356)
First-stage F-stats	20.569	10.347	20.569	10.347
Observations	61326	61326	61326	61326
R-squared	0.884	0.884	0.891	0.891

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.

Appendix A Truncation Adjustment

Following Hall, Jaffe and Trajtenberg (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[52]. 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, Jaffe and Trajtenberg (2001) and Hall, Jaffe and Trajtenberg (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

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

[52] 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, Caves and Frazer (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:

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

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%[53]. 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[54]. 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.

[53] See Fact SheetResearch & Development by the Numbers, R&D Coalition.

[54] See Measuring Tax Support for RD and Innovation, OECD.

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[55]:

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.

[55] Detailed illustration and examples are provided in An Overview of California's Research and Development Tax Credit.

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.3, 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, Dorn and Hanson (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.4, 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.5. 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.6, 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[56] 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

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

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 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 Conceptual Framework of Technology Adoption

G.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.

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 $\Delta\pi(\omega^*) = \Delta f$ (Figure **??**). 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 as shown in Figure **??**. 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 (as shown in Figure **??**). 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.

G.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 $\Psi = \frac{1}{\sigma}QP^\sigma(\sigma\frac{c(w,r)}{\sigma-1})^{1-\sigma}$.

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 H Additional Figures and Tables

Figure A.1: Graphic Illustration

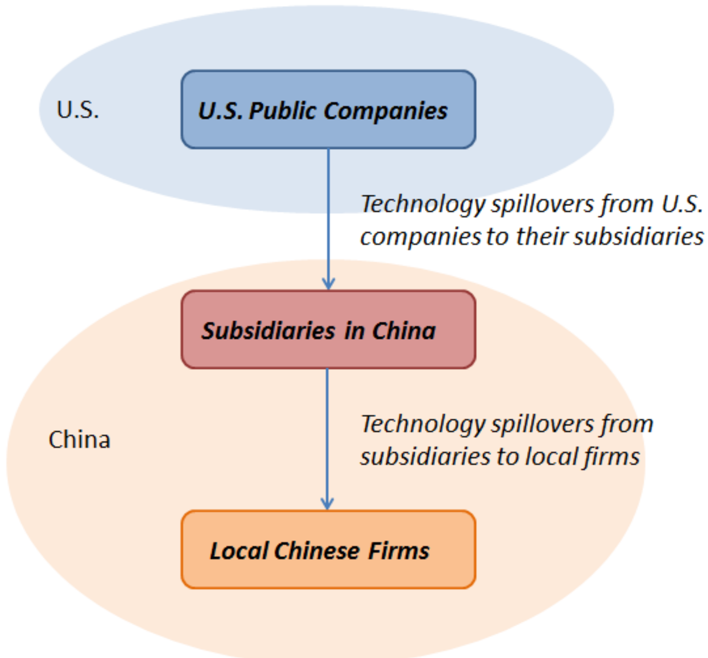


Figure A.2: Example of Name Matching Procedure

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.

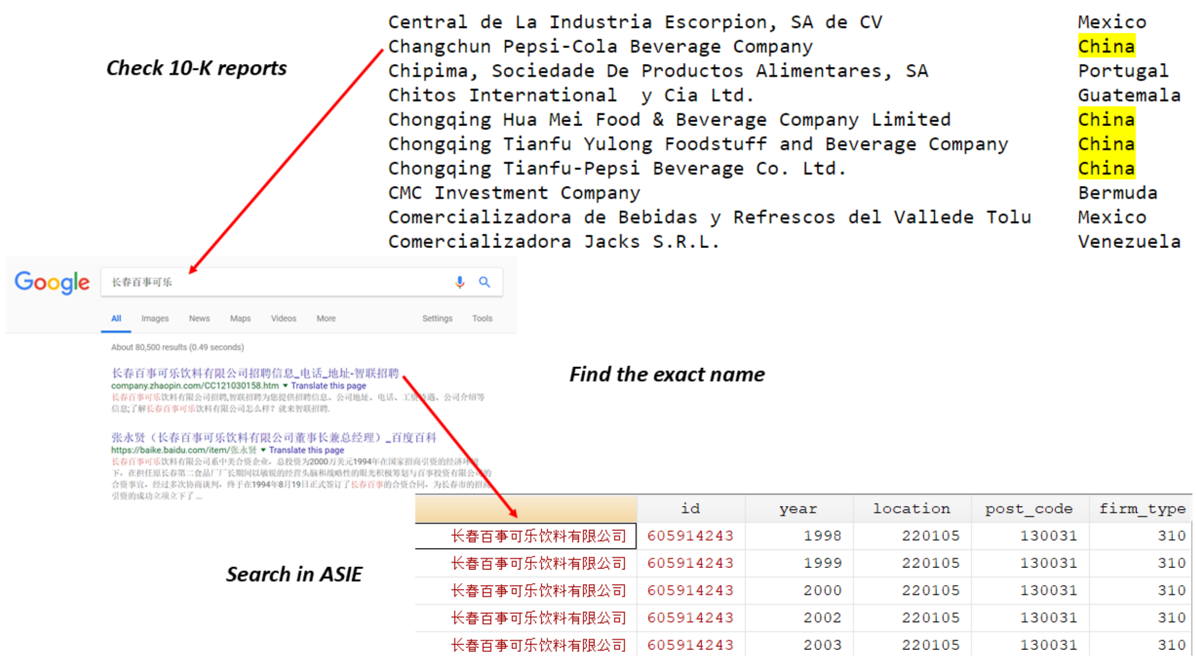


Figure A.3: Reflection: Line Plot of User Cost Comparison

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.

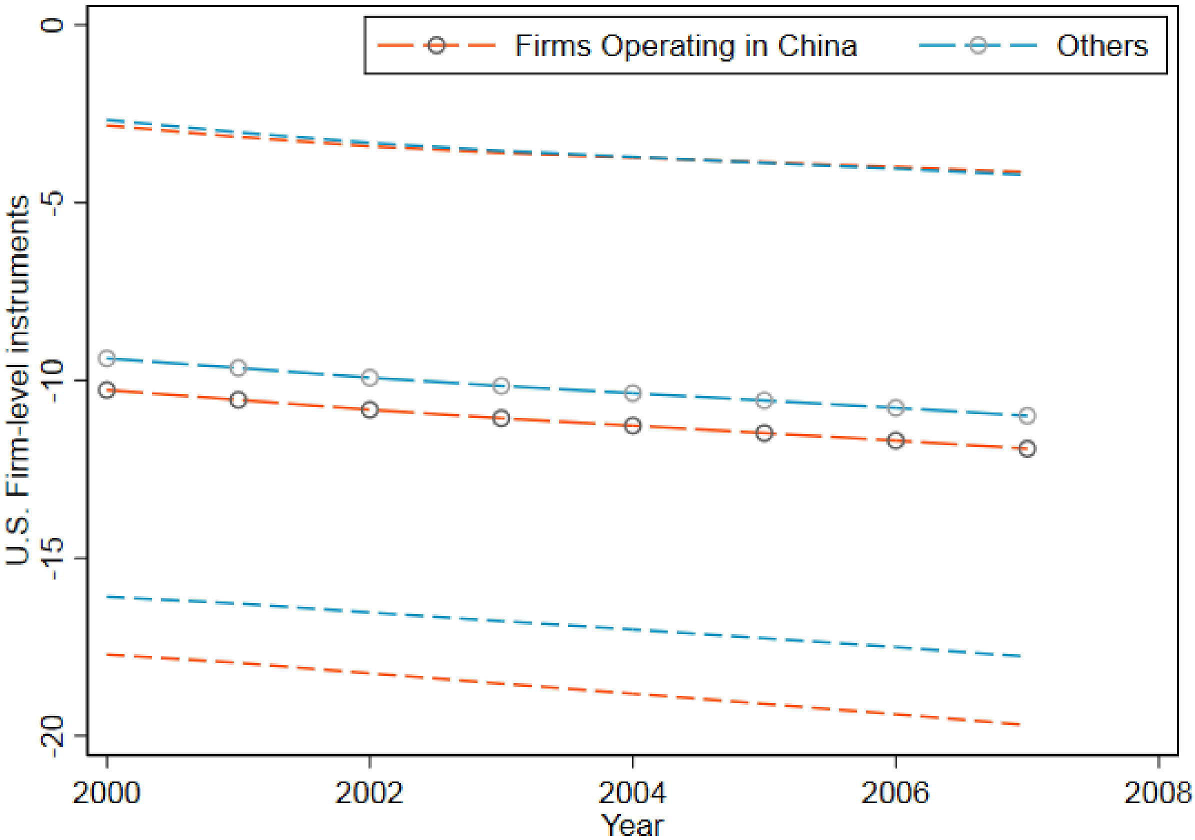
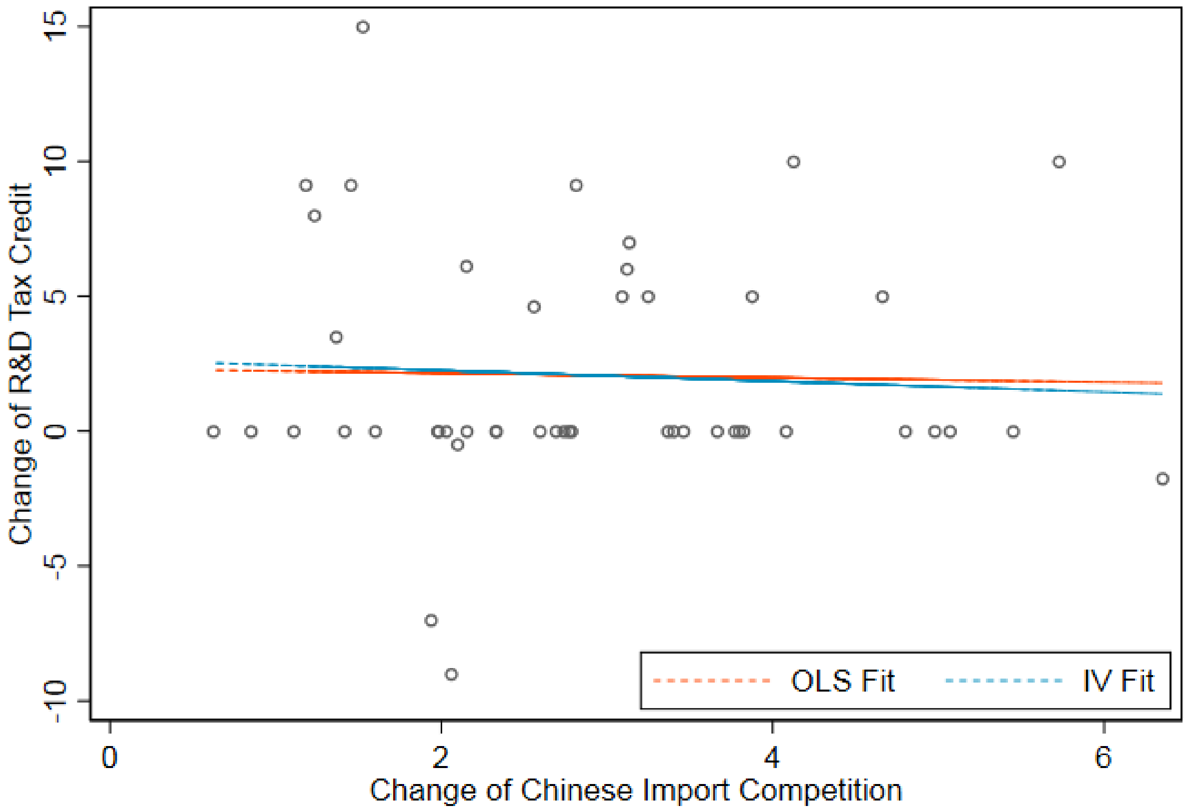


Figure A.4: Reflection: Chinese Import Competition and R&D Tax Credit (2000-2007)

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, Dorn and Hanson (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.



The OLS estimate is -.082 (.513); the IV estimate is -.201 (.598).

Figure A.5: Sorting: initial growth and instrument change

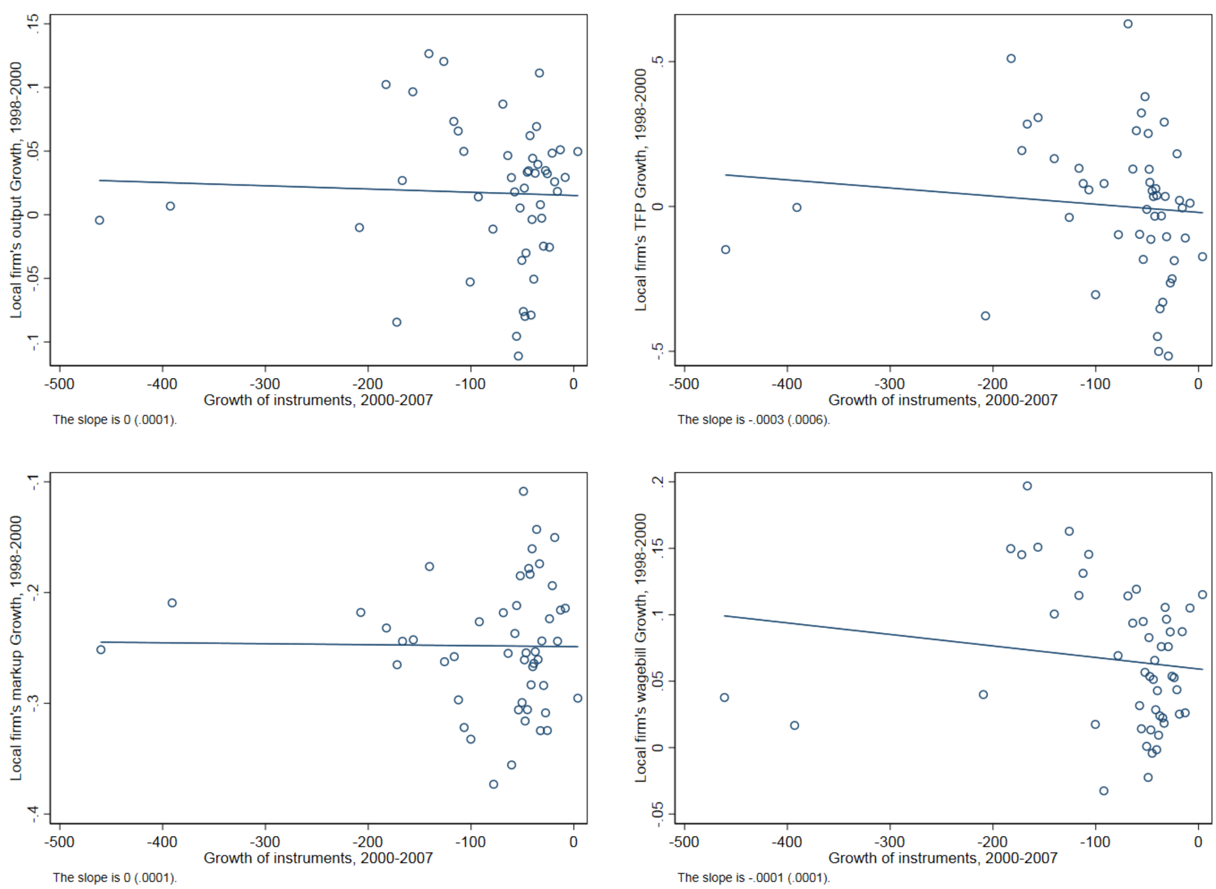


Figure A.6: Sorting: initial growth and spillover changes

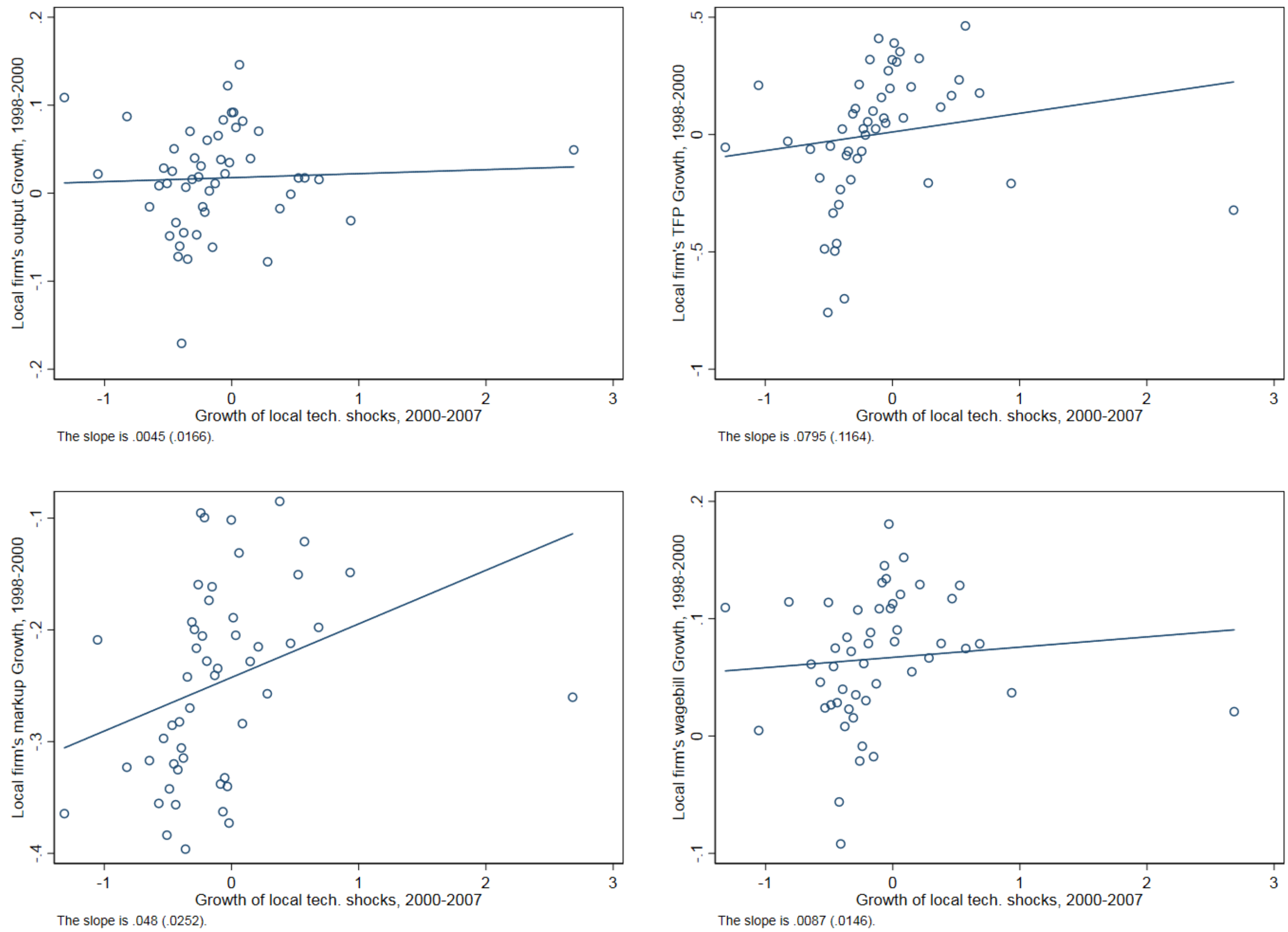
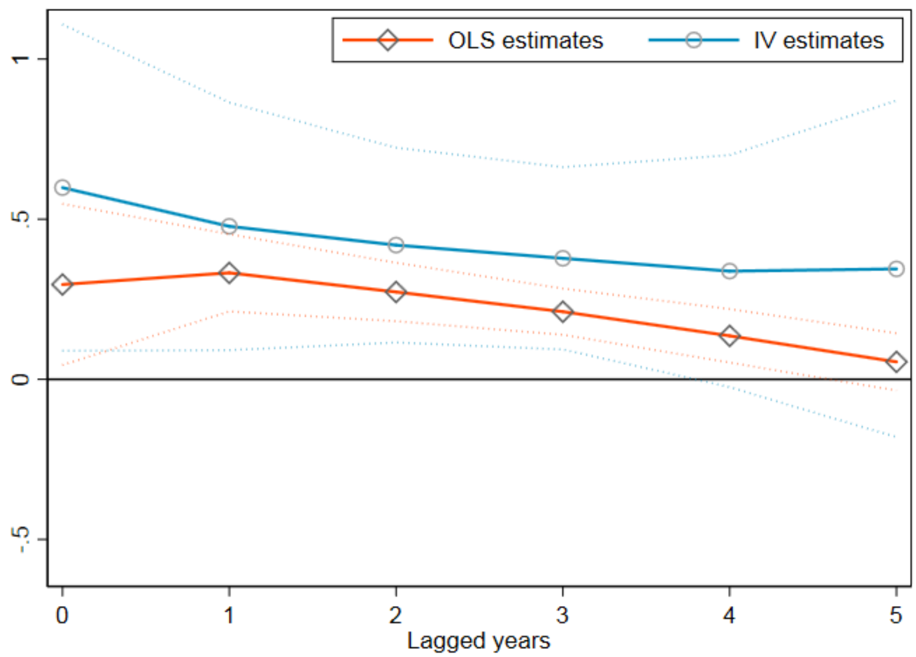


Figure A.7: The lagged effects of technology shocks

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

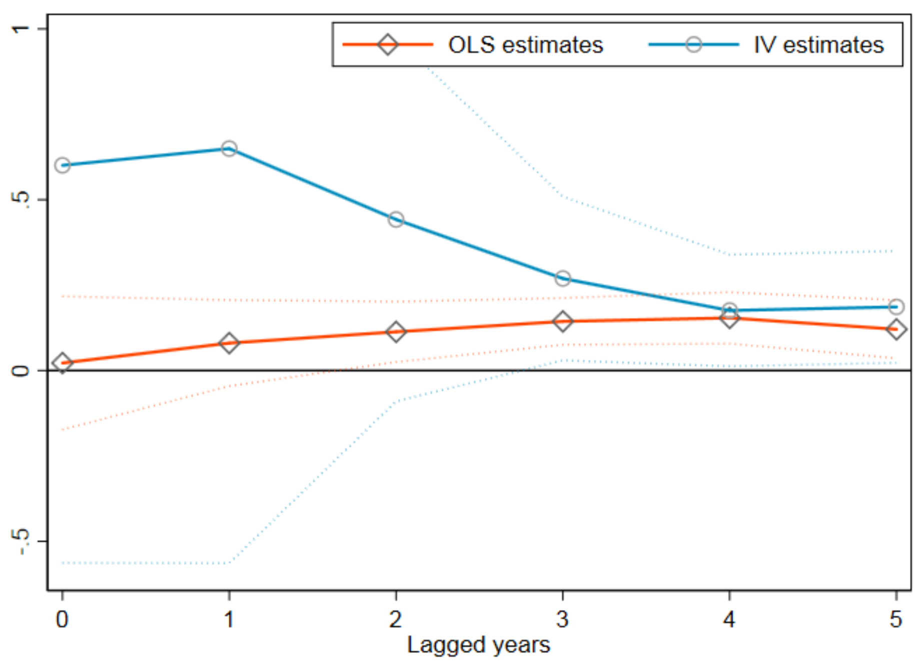


Figure A.8: Attenuation of local technology shocks with distance

The figure presents the relationship between the estimated local technology spillover effects and the choice of distance among counties' geographic centers. The point estimates and the 95% confidence interval are shown in the figure.

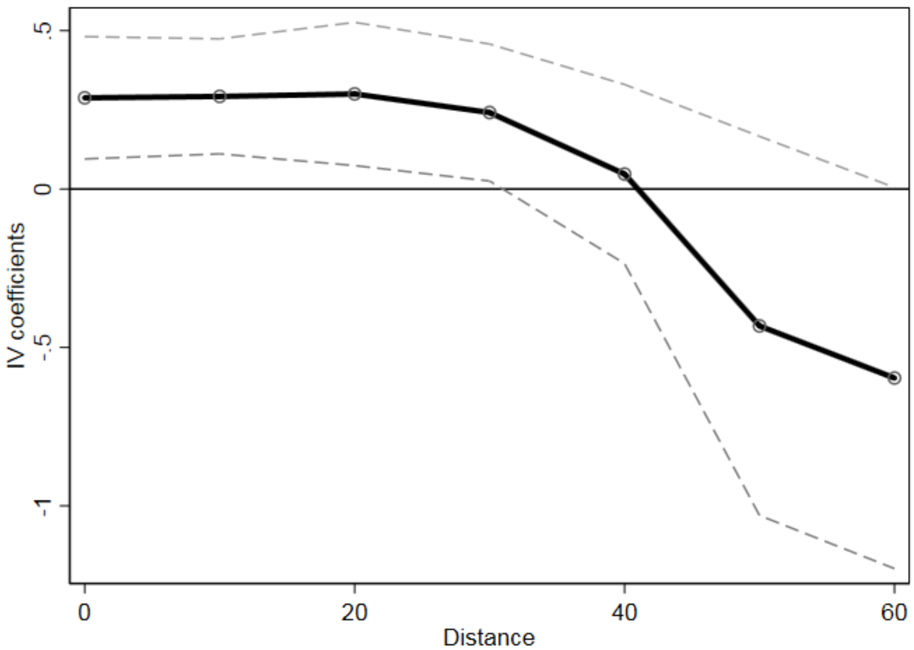


Table A1: Examples of U.S. Companies and their First Chinese Subsidiaries

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	310	670	213,901
Add ORBIS subsidiaries	322	725	242,401
Existing from 2000 to 2007	236	460	191,738
Match to patent data	210	370	161,425

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	-1.977***	-1.883***	-1.476***	-1.793***
	(0.0620)	(0.288)	(0.202)	(0.401)
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	1400	12900	1400
R-squared	0.839	0.930	0.866	0.971

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	*gp*	*w*	*m*	*roa*	*intangible*	*export*
	(1)	(2)	(3)	(4)	(5)	(6)
$TECH^{sub}$	0.350**	0.266*	0.325*	0.0328	1.222**	-0.434
	(0.135)	(0.135)	(0.183)	(0.0209)	(0.472)	(0.609)
Observations	1565	1565	1565	1565	1565	1565
R-squared	0.911	0.556	0.897	0.609	0.712	0.792

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	*gp*	*w*	*m*	*roa*	*intangible*	*export*
	(1)	(2)	(3)	(4)	(5)	(6)
$TECH^{loc}$	0.211*	0.320**	0.324*	0.0223	-0.0288	0.259
	(0.114)	(0.146)	(0.167)	(0.0185)	(0.332)	(0.361)
Observations	372547	372547	372547	372547	372547	372547
R-squared	0.910	0.490	0.886	0.564	0.719	0.859

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)
$TECH^{loc}$	-0.0456	-0.0177	-0.0282*	-0.0436**
	(0.0413)	(0.0428)	(0.0153)	(0.0216)
TFP deciles	-0.00381***	0.0183	-0.00818***	-0.0204
	(0.000678)	(0.0258)	(0.000702)	(0.0164)
$TECH^{loc} \times TFPdeciles$		-0.00582		0.00321
		(0.00693)		(0.00427)
Mean entry/exit	0.165		0.068	
Observations	371041	371041	371041	371041
R-squared	0.100	0.068	0.068	0.052

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)
$TECH^{sub}$	0.0151	0.640***	1.777***	1.661***
	(0.0862)	(0.236)	(0.574)	(0.504)
Observations	1565	1565	1565	1565
R-squared	0.675	0.592	0.895	0.922

Local technology shocks, tfpq				
Dependent variables	μ	*tfpq1*	*tfpq2*	*tfpq3*
	(1)	(2)	(3)	(4)
$TECH^{loc}$	-0.0704	0.508**	1.239**	1.408***
	(0.0780)	(0.203)	(0.479)	(0.486)
Observations	375454	375454	375454	375454
R-squared	0.615	0.578	0.882	0.886

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		Δhs_ratio, 2000-2005		
	(1)	(2)	(3)	(4)
$\Delta TECH^{loc}$, 2000-2005	0.0198**	0.0399**	0.0165**	0.0254*
	(0.00850)	(0.0176)	(0.00809)	(0.0150)
Weighting	No	No	Yes	Yes
First-stage F		11.412		15.953
Observations	202	202	202	202
R-squared	0.015	-0.000	0.016	0.012

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*	μ
	(1a)	(2a)	(3a)	(4a)
$TECH^{sub}_{R\&D}$	0.430**	0.304**	0.294***	0.00605
	(0.200)	(0.119)	(0.106)	(0.0682)
Observations	1565	1565	1565	1565
R-squared	0.666	0.598	0.580	0.704
Panel B. Local R&D shocks				
Dependent variables	*va*	*tfpr*	*lb*	μ
	(1b)	(2b)	(3b)	(4b)
$TECH^{loc}_{R\&D}$	1.019***	0.699***	0.695***	0.157
	(0.383)	(0.258)	(0.248)	(0.136)
Observations	375454	375454	375454	372424
R-squared	0.675	0.578	0.565	0.790

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	0.879***		0.637***	
	(0.225)		(0.232)	
Emp. shocks		0.779***		0.561***
		(0.237)		(0.212)
Observations	1435	1435	1435	1435
R-squared	0.705	0.706	0.639	0.640

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	*tfpr*	μ	*tfpr*	μ
	(1)	(2)	(3)	(4)
$TECH^{sub}$	0.365**	0.00198		
	(0.142)	(0.105)		
$TECH^{loc}$			0.288**	0.0408
			(0.132)	(0.0799)
Observations	1565	1564	375454	375454
R-squared	0.707	0.748	0.644	0.803

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
$TECH^{loc}$	1.515**	1.830	0.967**	1.224
	(0.611)	(1.353)	(0.403)	(0.868)
$TECH^{loc}$ X OS shares	-1.625**	-1.255	-0.994**	-0.882
	(0.698)	(1.872)	(0.469)	(1.187)
First-stage F-stats		8.02		8.02
Observations	229535	229535	229535	229535
R-squared	0.666	0.665	0.572	0.571

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.