Gravity of Intermediate Inputs in Productivity Spillovers: Evidence from Foreign Direct Investment in China

Yiqing Xie* Xiao Wang†‡§

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Abstract

The literature on the effect of multinational firms on the productivity of domestic firms has received wide attention; however, the exact channel of productivity spillover at a more micro firm level is under-explored. Based on a multi-sector production model, we examine heterogeneous productivity spillovers through the channel of upstream foreign direct investment (FDI) inputs at the firm level. We construct a firm-level distance statistic for the upstream FDI and

*Institute of China Studies, Shanghai Academy of Social Sciences, 1610 West Zhongshan Road, Shanghai, China, 200235. Email: yiqingxie@gmail.com

†International Institute of Finance, School of Management, University of Science and Technology of China, 96 Jinzhai Road, Hefei, China, 230026. Email: iriswx@ustc.edu.cn

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estimate the gravity of inputs: A firm is more productive if it gains access to more FDI inputs (general productivity-enhancing effect) and is geographically closer to upstream FDI firms (proximity effect). We find in the 2000-2007 Chinese firm data that (i) if a domestic firm's FDI input share increases by 1 percentage point, then its productivity is increased by 2.02%, and (ii) if the firm's distance from upstream FDI firms is 10% greater, then its productivity is reduced by 0.59%. The results are robust after controlling for FDI firm location selection bias and other productivity spillover channels.

JEL Classifications: F15, F21, F23, F61, F63

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1 Introduction

Foreign direct investment (FDI) has been surging into developing countries in the past 20 years. In China, for example, foreign capital in the manufacturing sector has more than tripled between 2000 and 2007. A natural question arises: does doing business with FDI firms increase a domestic firm's productivity? If so, how does the positive externality from FDI firms transfer to domestic firms? An ideal method of exploring the channel of productivity spillover is to examine the business-to-business transactions between FDI and domestic firms. However, firm-level transaction data are difficult to find. Mainstream research relies on the time variation in FDI inflow, which is identical for all firms in a specific industry, to identify the average FDI spillovers on domestic firms at the industry level.[1] However, it is still unclear whether the spillover effect is heterogenous across individual firms or how to quantify the difference in spillovers among them.

This paper aims to examine the channels of productivity spillover at the firm level. As the advanced technology embodied in inputs produced by FDI firms (thereafter FDI inputs) can improve domestic firms' productivity (Keller and Yeaple, 2013) and firms' use of FDI inputs is measurable, we explore the spillovers through the channel of FDI inputs. To be more specific, we examine the heterogenous spillovers due to variations in firms' geographic access to FDI inputs. In a multi-sector production model, we are able to decompose the measured total factor productivity of a firm into three components: (i) a technology parameter, (ii) a homogeneous productivity-enhancing effect from FDI inputs, and (iii) a heterogeneous proximity effect that depends on a forward distance statistic, which is defined as a weighted average geographical distance toward upstream FDI firms with FDI sales ratio as the weight. We denote the latter two effects as the gravity effect of intermediate inputs, including the portion of FDI inputs and the effects of the forward distance statistic productivity spillovers for a domestic firm.

[1] See Javorcik (2004) and Liu (2008) on the channel of the same, upstream, and downstream industries. Hale and Long (2011) and Gorodnichenko, Svejnar, and Terrell (2014) find mixed evidence of positive productivity spillovers from FDI firms. Also see Aitken and Harrison (1999) on the channel of financing and Fosfuri, Motta, and Ronde (2001) on the channel of workers' mobility.

We employ Chinese firm-level data from 2000 to 2007 to estimate the heterogenous productivity spillovers at the firm level. The time period of the data covers China's accession to the World Trade Organization (WTO) in 2001 and the substantial FDI regulatory changes that followed. As more FDI flows into China, the entry, exit, and market share change of upstream FDI firms alter the weights in the forward distance statistic, while the pairwise geographic distance between a FDI firm and the domestic firm is constant over time. Therefore, the forward distance statistic is changing for the same domestic firm across years. Our benchmark OLS results show that if a domestic firm's FDI input share increases by 1 percentage point, its productivity increases by 2.02%. If the weighted average distance is 10% less, then the domestic firm is 0.59% more productive. We also consider the potential endogeneity problem in which FDI firms may select entry locations or adjust their domestic sales, thereby affecting the weight of the forward distance statistic. Given that cities are exposed to FDI-supporting policies unevenly due to their different industry compositions, we construct an instrumental variable for the proximity effect: a weighted average distance toward FDI input suppliers, with the city-industry level FDI policy exposure as its weight. The instrumental variable regression results are consistent with the benchmark, and both effects are larger in magnitude than the benchmark. Furthermore, our empirical results are robust after we control for the local labor and capital-good market externalities, the upstream domestic firm spillovers, and imported input effects and limit our sample within domestic firms that entered before China's accession to the WTO.

This paper contributes to four strands of the literature on productivity spillovers. First, it helps to quantify heterogeneous productivity spillovers at the firm level due to variations in the access to FDI inputs, and these spillovers are in addition to the average forward spillovers identical to all firms in a given industry.[2] Second, the estimated impact of firms' geographic access to FDI inputs on productivity spillovers adds to the literature trend that discusses how the geographical

[2] Also see Liu et al. (2009) and Wang (2010) for the forward channel in China. Halpern and Murakozy (2007) discuss the role of distance in productivity spillovers for Hungarian firms but do not separate the distance effect from overall productivity spillovers.

remoteness impedes technology diffusion at the country level (Keller, 2002). Compared with including the spatial correlation in the intra-industry spillovers[3], this paper directly estimates the effect of a domestic firm's forward distance statistic on receiving upstream FDI spillovers. Third, the estimated gravity effect identifies a specific channel of domestic firms' benefit from the agglomeration, namely, firms' geographic clustering.[4] Compared with the agglomeration measure for a region or for an industry (Alfaro and Chen, 2014), we are able to investigate the firm-level agglomeration effect induced by the exogenous FDI policy shocks associated with China's accession to the WTO. Fourth, complementing the literature on the role of imported inputs in enhancing firm-level productivity, this paper shows that the firm-level productivity can be improved if domestic firms employ more inputs produced by FDI firms, especially those of developing countries that have already attracted a large amount of FDI.

The remainder of the paper is organized as follows. Section 2 builds an illustrative model and proposes the benchmark estimation equation. Section 3 describes the data and the construction of the key variables. Section 4 displays the benchmark results and the robustness checks. Section 5 presents the conclusions.

2 Model

In this section, we present a parsimonious multi-sector production model with heterogeneous firms. This model aims to provide a framework that lays out the firm production function and allows for the derivation of an estimating equation for the regression analysis. In the model, we decompose the measured total factor productivity of a domestic firm into three components: a firm-level technology parameter, the general productivity-enhancing effect from upstream FDI firms, and the proximity effect that varies with the firm's geographical accessibility to upstream FDI firms. We then propose the benchmark estimation equation that identifies these two effects.

[3]Baltagi, Egger, and Kesina (2016).

[4]Ellison, Glaeser, and Kerr (2010) review the spillover channels of FDI firms and the agglomeration effect.

2.1 *Illustrative model*

Production. An economy has I industries. There are a large number of domestic and FDI firms in each industry, and each firm belongs to exactly one industry. In industry i ($i = 1, 2, \cdots, I$), each of these firms, which are indexed by h, differs in technology A_h. Firm h employs capital K_h, labor L_h, and intermediate inputs X_h to produce output Y_h according to the production function:

$$Y_h = A_h \big(K_h\big)^{\gamma_k} \big(L_h\big)^{\gamma_l} \big(X_h\big)^{\gamma_x}, \tag{1}$$

where γ_k, γ_l, and γ_x are production parameters. We assume that two primary inputs (capital and labor) are homogeneous and firm h can acquire them in perfectly competitive markets.

Intermediate inputs. Firm h acquires its inputs from a competitive factor market. The intermediate demand of firm h, X_h, has a three-tiered structure, with the first tier being a Cobb-Douglas function over its demand from the upstream industries:

$$X_h = C_{i1} \prod_j \big(X_{jh}\big)^{\alpha_{ji}},$$

where X_{jh} denotes the input from an upstream industry j; α_{ji} represents the input share from industry j and satisfies $\sum_j \alpha_{ji} = 1$; and C_{i1} is a constant, with $C_{i1} = \prod_j \alpha_{ji}^{\alpha_{ji}}$.

The second tier of the input demand is the demand for inputs from a specific industry j:

$$X_{jh} = C_{i2} \big(X_{Djh}\big)^{1-\kappa_j} \big(\eta X_{Fjh}\big)^{\kappa_j}.$$

This input consists of two varieties produced by domestic and FDI firms, X_{Djh} and X_{Fjh}, respectively. We assume that η ($\eta > 1$) measures the advantage of spending one unit of expenditure on FDI inputs rather than domestic counterparts, namely, the productivity-enhancing effect of FDI inputs. Halpern et al. (2015) document that imported inputs can enhance the productivity of domestic firms through their quality and the consequent effectiveness in production. Similarly, the productivity-enhancing effect represents the effectiveness of FDI inputs, e.g., the high quality of FDI inputs and the associated complementary knowledge from using them help to improve downstream firms' productivity. $\kappa_j \in (0,1)$ is the parameter that measures the importance of FDI inputs in industry j. A higher κ_j denotes growth in the upstream FDI market share. C_{i2} is a constant, and $C_{i2} = (1-\kappa_j)^{1-\kappa_j}\kappa_j^{\kappa_j}$.

In the third tier of the input demand, we focus on the impacts of FDI intermediate inputs, assuming that inputs from domestic firms are perfect substitutes.[5] Firm h demands X_{fh} from firm f that belongs to the FDI firm set Ω_j in industry j:

$$X_{Fjh} = \Big[\sum_{f\in\Omega_j} \omega_f^{\frac{1}{\theta}} X_{fh}^{\frac{\theta-1}{\theta}}\Big]^{\frac{\theta}{\theta-1}},$$

where ω_f is the share of intermediate inputs sold by firm f, $\sum_{f\in\Omega_j}\omega_f = 1$, and θ is the elasticity of the substitution, $\theta > 1$.

Following Keller (2002) and Ellison et al. (2010), the productivity-enhancing effect of FDI inputs is weakened if T_{fh}, which is the distance between firm h and a FDI firm denoted by f, is larger because firm h is hindered from receiving spillovers from its input supplier f, such as hand-to-hand training, on-time technology support, and complementary services.[6] We follow Keller (2002) to choose an explicit model that links the geographic access to FDI inputs with firms' productivity spillover. Specifically, we model that distance T_{fh} affects the trade cost of FDI inputs for firm h.[7]

[5] We relax this assumption in the robustness check of estimation results.

[6] Keller and Yeaple (2013) provide evidence that in addition to the technology codified in the inputs, productivity transfer also needs the communication associated with input supply. The communication is more effective and less prone to errors if input suppliers and users can have more direct information exchange. Markusen and Trofimenko (2009) also indirectly prove this communication channel by confirming the positive effects from the presence of foreign experts in domestic firms.

[7] Alternatively, we can model that the distance affects the FDI use directly: $X_{Fjh} = \big[\sum_f \omega_f^{1/\theta}\big(X_{fh}/P(T_{fh})\big)^{(\theta-1)/\theta}\big]^{\theta/(\theta-1)}$, and all results hold.

Firm h incurs a trade cost $P(T_{fh})$ to obtain one unit of FDI input, $P(T_{fh}) \equiv \big(C - T_{fh}\big)^{1/(1-\theta)}$, where C is a constant.[8] Note that the trade cost $P(T_{fh})$ grows with distance T_{fh} given $\theta > 1$.

Firm h minimizes its expenditure M_h on intermediate inputs. We relegate the derivation details for the cost-minimizing problem in online Appendix A and display the solutions in the three-tier structure. Denoting the prices of domestic and FDI inputs in industry j as P_{Dj} and P_{Fj} respectively, in the third tier, the domestic input price for firm h is P_{Dj} and the FDI input price for firm h is $P_{Fjh} = P_{Fj} G_{jh}$, where $G_{jh} \equiv \big[\sum_{f \in \Omega_j} \omega_f P(T_{fh})^{1-\theta}\big]^{1/(1-\theta)}$. In the second tier, the input price from industry j is $P_{jh} = P_j \big(\eta\big)^{-\kappa_j} \big(G_{jh}\big)^{\kappa_j}$, where P_j is the industry price index and $P_j = \big(P_{Dj}\big)^{1-\kappa_j} \big(P_{Fj}\big)^{\kappa_j}$. In the first tier, the input price for firm h is $P_h^x = \prod_j \big(P_{jh}\big)^{\alpha_{ji}}$. We then rewrite the input demand of firm h based on its input expenditure and price:

$$X_h = M_h / P_h^x = M_h \prod_j \big(P_j\big)^{-\alpha_{ji}} \prod_j \big(\eta^{\kappa_j}\big)^{\alpha_{ji}} \prod_j \big((G_{jh})^{-\kappa_j}\big)^{\alpha_{ji}}.$$

Taking logs of the input demand and employing the Taylor approximation for T_{fh},[9] we obtain the following:

$$x_h = m_h - \sum_j \alpha_{ji} p_j + ln\eta \sum_j \alpha_{ji} \kappa_j - \frac{1}{\theta - 1} \sum_j \alpha_{ji} \kappa_j \sum_f \omega_f T_{fh}, \tag{2}$$

where the lower case letters indicate the logged variables.

[8]We need $P(T_{fh}) > 0$, and $P(T_{fh})$ can be approximated by the Taylor expansion. Online Appendix A show that $\sum_f \omega_f T_{fh} < C \leq \sum_f \omega_f T_{fh} + 2$ satisfies these conditions.

[9]We employ the Taylor expansion around $C - \sum_f \omega_f T_{fh} = 1$. The details are in online Appendix A.

2.2 *Benchmark estimation equation*

We take the log of the production function (1) and substitute Eq. (2) into it. To generate an empirically testable estimation equation, we add the time subscript t to each time-varying variable:

$$\begin{aligned} y_{ht} - \gamma_k k_{ht} - \gamma_l l_{ht} - \gamma_x \big(m_{ht} - \sum_j \alpha_{ji} p_{jt}\big) \\ = a_{ht} + \underbrace{\gamma_x ln(\eta) \sum_j \alpha_{ji} \kappa_{jt}}_{\text{General productivity-enhancing effect}} \underbrace{- \frac{\gamma_x}{\theta - 1} \sum_j \alpha_{ji} \kappa_{jt} \sum_{f \in \Omega_{jt}} \omega_{ft} T_{fh}}_{\text{Proximity effect}}, \quad (3) \end{aligned}$$

where the lower case letters indicate the logged variables. The left hand side of Eq. (3) is the measured total productivity, and the right hand side can be decomposed into a firm-level technology a_{ht} and two transmission channels of productivity spillovers: the general productivity-enhancing effect that describes how domestic firms benefit from the overall contribution of FDI in intermediate inputs and the proximity effect that depicts how domestic firms that are geographically remoter to upstream FDI firms benefit less from the forward productivity spillover. Below we describe how we define and measure each variable in Eq. (3).

Total factor productivity. The left hand side of Eq. (3) is the measured productivity $ln\big(TFP^m_{ht}\big)$:

$$ln\big(TFP^m_{ht}\big) \equiv y_{ht} - \gamma_k k_{ht} - \gamma_l l_{ht} - \gamma_x \big(m_{ht} - \sum_j \alpha_{ji} p_{jt}\big), \quad (4)$$

and we define $m^r_{ht} \equiv m_{ht} - \sum_j \alpha_{ji} p_{jt}$ as the real intermediate input expenditure of firm h observed in data [10]. The coefficients in (4) may be affected by a_{ht} if firm h responds to the productivity shock when selecting inputs. We will discuss how to measure $ln\big(TFP^m_{ht}\big)$ in detail in the next section.

General productivity-enhancing effect. When more FDI flows into China or existing FDI firms

[10] The price index p_{jt} for industry j is the Producer Price Index (PPI) from the statistical yearbooks. It does not include "the general productivity-enhancing effect", which is represented by η because η measures the advantage of spending one identical unit of expenditure on FDI inputs rather than domestic counterparts. It also does not include "the proximity effect", which is represented by $\sum_j \alpha_{ji} \kappa_{jt} \sum_f \omega_{ft} T_{fh}$, because the PPI is generated from manufacturers' factory prices, which do not include distance-related trade cost.

have higher domestic sales, domestic firms can obtain access to more FDI intermediate inputs and therefore absorb more productivity spillovers. Adopting the definition of the forward channel in Javorcik (2004), we measure κ_{jt} as the weighted average portion of FDI firms' outputs that sell in the domestic market:

$$forward_{it} \equiv \sum_j \alpha_{ji}\kappa_{jt} = \sum_j \alpha_{ji} \frac{\sum_{f\in\Omega_{jt}} fshare_{ft} \cdot (Y_{ft} - EX_{ft})}{\sum_{f\in j}(Y_{ft} - EX_{ft})}, \tag{5}$$

where $fshare_{ft}$ is defined as the share of foreign capital for firm f in period t; and $(Y_{ft} - EX_{ft})$ is the difference between total sales and exports, equivalent to the domestic sales of firm f. The fraction term as a whole measures the relative importance of FDI in industry j in providing intermediate inputs to industry i. Overall, $forward_{it}$ averages the portions of FDI inputs in all upstream industries, which is weighted by the input usage ratio α_{ji} from the input-output matrix.

Proximity effect. Intuitively, firm h gains easier access to FDI inputs if new upstream FDI firms start operations near its location or if nearby existing FDI firms increase their market share. In contrast, the exit or shrinking sales of existing FDI firms impede firm h from acquiring FDI inputs. We formalize the idea of the proximity effect by constructing a forward distance statistic between firm h and its upstream FDI firms. We define the market share of intermediate inputs from FDI firm f as follows:

$$\omega_{ft} = \frac{fshare_{ft} \cdot \left(Y_{ft} - EX_{ft}\right)}{\sum_{f\in\Omega_{jt}} fshare_{ft} \cdot \left(Y_{ft} - EX_{ft}\right)}, \tag{6}$$

where $fshare_{ft}$ is firm f's foreign capital share. Substituting κ_{jt} from Eq. (5) and ω_{ft} from Eq. (6) into the last term of Eq. (3), firm h's forward distance statistic can be written as follows:

$$dist_{ht} \equiv \sum_j \alpha_{ji}\kappa_{jt} \sum_{f\in\Omega_{jt}} \omega_{ft} T_{fh} = \sum_j \alpha_{ji} \sum_{f\in\Omega_{jt}} \frac{fshare_{ft} \cdot \left(Y_{ft} - EX_{ft}\right)}{\sum_{f\in j}\left(Y_{ft} - EX_{ft}\right)} T_{fh}, \tag{7}$$

where $dist_{ht}$ is the weighted average distance between firm h and its upstream FDI firms. The weights consist of two tiers: α_{ji}, the input share from upstream industry j, and $\kappa_{jt} \cdot \omega_{ft} = fshare_{ft} \cdot \big(Y_{ft} - EX_{ft}\big) / \sum_{f \in j}(Y_{ft} - EX_{ft})$, the contribution of FDI firm f in providing inputs in industry j. Since most firm-level data do not provide detailed information on business-to-business transactions and therefore a firm-level input-output matrix is very rare, we believe this forward distance statistic could provide a good approximation for the firm-level accessibility to FDI intermediate inputs.

We should also note that the forward distance statistic $dist_{ht}$ reflects both the trade costs of shipping inputs across cities from FDI firms to domestic firms and the role of distance as a barrier to communication or knowledge diffusion. We are unable to differentiate the two types of trade costs, although the latter one is considered the "pure" productivity spillover barrier since we cannot directly observe the shipping costs across cities.

Benchmark estimation equation. Substituting Eq. (4), (5) and (7) into Eq. (3) and adding the control variables and the firm-level error term, we obtain the benchmark estimation equation:

$$ln\big(TFP^m_{ht}\big) = \beta_0 + \underbrace{\beta_1 forward_{it}}_{\text{General productivity-enhancing effect}} + \underbrace{\beta_2 dist_{ht}}_{\text{Proximity effect}} + \mathbf{x}_{ht} + \mu_h + \epsilon_{ht}, \tag{8}$$

where $\mathbf{x}_{ht}$ is the vector of control variables; μ_h is the firm fixed effect; and ϵ_{ht} is the independently and identically distributed (i.i.d.) shock.

The coefficient β_1 represents the general productivity-enhancing effect identical to firms in industry i. We predict $\beta_1 > 0$ because the prominence of upstream FDI could strengthen the productivity of downstream domestic firms through their intermediate inputs. The coefficient for the term $dist_{ht}$, β_2, demonstrates the heterogenous proximity effect at the firm level. We predict $\beta_2 < 0$ because the geographical remoteness reduces the productivity spillovers to domestic downstream firms. Coefficients β_1 and β_2 jointly describe the gravity effect of FDI intermediate inputs, not only the relative importance of FDI intermediate inputs matters but also the domestic firms' geographic proximity to upstream FDI firms, which plays an important role on the productivity spillovers through the availability of FDI intermediate inputs.

Remark. We can also derive the benchmark estimation equation with an industry general effect and a firm-specific geographic proximity effect if the domestic X_{Djh} and foreign inputs X_{Fjh} are combined in a CES function. The details are provided in Online Appendix B. Another point we want to mention is that Eq. (8) is consistent with the estimation equation in Javorcik (2004) if all distances between domestic firms and upstream FDI firms are identical: $T_{fh} = T$. Specifically, the firm-specific effect of forward distance statistic becomes a constant: $\sum_j \alpha_{ji}\kappa_{jt} \sum_f \omega_{ft} T_{fh} = T \sum_j \alpha_{ji}\kappa_{jt} = T forward_{it}$, using $\sum_{f\in\Omega_{jt}} \omega_{ft} = 1$. Then, the benchmark estimation equation (8) degenerates to the following:

$$ln\big(TFP^{m}_{ht}\big) = \beta_0 + \beta_1 forward_{it} + \mathbf{x}_{ht} + \mu_h + \epsilon_{ht}.$$

3 Data and Estimation Strategy

In this section, we describe the data set, specify our estimation strategy on the potential FDI location endogeneity problem, and display the summary statistics of key variables.

3.1 *Data*

China is an ideal natural experimental field to examine the gravity effect of intermediate inputs in productivity spillovers because China has a relatively complete industrial structure and has attracted a large volume of FDI into almost all manufacturing industries. Our dataset covers large-scaled non state-owned enterprises with sales revenue greater than 5 million Chinese yuan and all state-owned enterprises with no scale limit from the manufacturing sector in China.[11] Between 2000 and 2007, approximately 122,000 firms on average in each year satisfied the above criterion. This firm-level dataset is collected through Annual Surveys of Industrial Production by National

[11] Approximately US $600,000 at the exchange rate in 2005. More than 75% of SOEs have sales revenue over 5 million Chinese yuan.

Bureau of Statistics of China. All firms that satisfy the criteria on sales are legally obligated to report to National Bureau of Statistics of China.

In addition to complete information on the three major accounting statements (balance sheet, income statement, and cash flow statement), the dataset also contains information on location, ownership, and employment. We exclude observations with missing or negative values of sales, employment, or firm age, which reduces the sample to 928,387 firm-year observations (with 611,248 Chinese domestic firm-year observations) in 30 manufacturing industries. Although it does not cover firms with sales revenue less than 5 million Chinese yuan, the sample should reflect all major characteristics of FDI at the firm level in China because multinational firms tend to be large in size (Helpman, Melitz, and Yeaple, 2004).

3.2 *Empirical strategy*

During the data time period, China acceded to the WTO in 2001, and the FDI policies were adjusted accordingly. While the intensive FDI-encouraging policies exogenously boosted FDI inflow in China, multinational firms might endogenously determine their entry location for new affiliates or adjust domestic sales of existing ones. In this subsection, we first provide some supporting evidence on the relative exogeneity of FDI-boosting policies after China's accession to the WTO to justify the assumption in the benchmark regression. Then, we introduce the instrumental variable estimation strategy by applying the FDI-boosting policies to correct for the potential bias caused by FDI firms' endogenous location choice.

3.2.1 *FDI policy shocks*

China has started the open trade policy and allowed inward FDI since 1978, although the volume and industries of FDI were strictly limited initially. After a long-term bargaining process, China joined the WTO in 2001 and accelerated its opening to the world. The central government then substantially revised "the Catalogue for the Guidance of Foreign Investment Industries" (the Catalogue henceforth) in 2002, in accordance with China's commitment during the negotiation process for its WTO membership. The changes in the Catalogue encouraged the flow of FDI to more industries that were previously restricted.

The timing of China's accession to the WTO is relatively random, and the corresponding FDI policy changes are difficult to precisely predict. China has submitted its application to the predecessor of the WTO, the General Agreement on Tariffs and Trade (GATT), as early as in 1986. After the WTO replaced the GATT in 1995, China resubmitted its application and thereafter experienced 18 rounds of formal meetings for multilateral negotiations before its membership was approved in 2001.[12] Facing the long-term bargaining process, market participants found it almost impossible to predict the exact timing of the WTO membership approval for China. Lu et al. (2017) documented that after China's accession to the WTO, the central government liberalized one quarter of 424 four-digit manufacturing industries to FDI in the Catalogue with different degrees: An industry might switch from "prohibited" or "restricted" to "permitted" or "encouraged". Again, it was difficult for investors to forecast accurately the industries that would be open and the detailed regulation changes in those industries.

We compare the average domestic sales of FDI firms for each city in 2000 (before the WTO accession) and 2007 (after the WTO accession), as shown by Figure 1. We divide the domestic sales of FDI firms into 5 groups according to different quantiles of domestic sales in 2000 and depict the average domestic sales in each city according to the group each city falls into, with a darker color indicating a higher level of sales.[13] In Figure 1, more city dots appear and the city dots are darker in 2007 than in 2000, showing that these the cities had a significant increase in domestic sales of FDI firms.

[12]Data resource: www.wto.org.

[13]Specifically, for both 2000 and 2007, the first group of the cities with the lightest points has domestic sales of FDI firms less than 1.02 million RMB (25% in 2000), the second group includes the cities with domestic sales of FDI firms between 1.02 and 5.90 million RMB (25% to 50% in 2000), the third group is between 5.90 and 17.13 million RMB domestic sales of FDI firms (50% to 75% in 2000), the fourth group is between 17.13 and 218.07 million RMB (50% to 75% in 2000) and the last group with the darkest points represents the cities with domestic sales of FDI firms exceeding 99% in 2000 (above 218.07 million RMB).

[Insert Figure 1 here]

With the plausible exogenous changes in FDI regulations, the FDI inflow has grown explosively during the data time period. Moreover, locations were exposed to heterogenous FDI-encouraging policies due to their different industrial compositions. FDI then surged into locations with more favorable FDI policies.

Specifically, we calculate the FDI-favoring policy index as $PC_{jct}= w_{jc1998}POL_{jt}$, where POL_{jt} is the policy score for industry j in year t, and it ranges from 1 to 4, with a higher score representing a higher degree of FDI-favoring policy.[14] There are three tiers of administrative areas in China: province, city, and district. As the administrative divisions at the district level have changed frequently during the time period, we can only compute the policy exposure at the city level. The weight w_{jc1998} is the FDI capital ratio of each industry in that city in 1998, which is before China's accession to the WTO.[15] Similar to the methodology in Topalova (2010), we choose the FDI share weight earlier than China's accession to the WTO to avoid the endogeneity problem in which the induced FDI could change the foreign capital share of an industry.

We then delineate more supporting evidence that FDI flowed into regions that were exposed to intensive FDI-favoring policies. Panel a of Figure 2 depicts the positive correlation between the FDI-favoring policy index PC_{jct} and the FDI entry at the city-industry level. We lag the policy index by one year as it took time for FDI to enter after the policies became effective. Panel b of Figure 2 exhibits a similar pattern that FDI-favoring policies exert positive influence on domestic sales by FDI firms. We display the policy index and sales in the same period because sales can be adjusted for time.

[Insert Figure 2 here]

[14]If the FDI policy specifies an industry as "prohibited", "restricted", "permitted", or "encouraged", we assign the policy score for this industry as 1, 2, 3, or 4 respectively.

[15]The pattern is robust if we use industry production share of a city as the weight.

3.2.2 *Endogenous choices by FDI firms*

As multinational firms may endogenously determine their entry location for new affiliates or adjust domestic sales of existing ones, the FDI input share ω_{ft} used in the construction of the distance statistic $dist_{ht}$ suffers from the endogeneity problem, and the empirical estimation results from Eq. (8) may be biased. We employ the instrumental variable regression to alleviate the endogeneity problem. We have shown in Figure 2 that FDI inflows are abundant in cities that are exposed to intensive supporting policies. The FDI input share of a domestic firm is also positively affected if its upstream FDI suppliers are exposed to encouraging policies. Therefore, we construct an industry-city level forward FDI policy index and use it as the weight to generate a forward policy weighted distance statistic $dist^p_{ht}$ to instrument $dist_{ht}$.

Specifically, $dist^p_{ht}$ is constructed in two steps. First, we construct the forward FDI policy index PE_{ict} by aggregating all upstream industry policy indexes in city c: $PE_{ict} \equiv \sum_j \alpha_{ji} PC_{jct}$. Second, we construct the instrument by replacing the FDI sales weight with the rescaled forward FDI policy index:

$$dist^p_{ht} \equiv \sum_c T_{ch} PE_{ict}/100. \tag{9}$$

where T_{ch} is the distance to upstream FDI firms in city c.[16] As the FDI policy in $dist^p_{ht}$ ranges between 1 and 4 and the FDI input share ω_{ft} in $dist_{ht}$ can be less than one percent, we rescale the policy index PE_{ict} (through dividing by 100) to the same magnitude of the FDI input share ω_{ft}, to guarantee that the instrument $dist^p_{ht}$ is comparable with the forward distance statistic $dist_{ht}$.

After constructing the instrument, the first stage of the instrumental variable regression is as

[16]Because the forward FDI policy index can only be specified at the city level but not at the district level, the distance measure T_{ch} in the instrumental variable is also calculated at the city level.

follows:

$$dist_{ht} = \beta_{p0} + \beta_p dist^p_{ht} + \mathbf{x}_{ht} + \mu_h + \nu_{ht},$$

where ν_{ht} is the measurement error.

As a robustness check, we consider an alternative specification that supposes both $foward_{it}$ and $dist_{ht}$ in the benchmark regression (8) may be endogenous. Then, we need two instruments for these two endogenous regressors. In addition to $dist^p_{ht}$, we construct an industry level forward FDI policy index $FPOL_{it}$ that can affect upstream FDI firms' entry and sales:

$$FPOL_{it} = \sum_j \alpha_{ji} POL_{jt},$$

where $FPOL_{it}$ is a weighted sum of FDI policies in all upstream industries of industry i with the input share weight α_{ji}. As more FDI-encouraging policies took effect after China's accession to the WTO, the exogenous changes in $FPOL_{it}$ can affect the upstream FDI firms' entry and sales and thus affect the portion of FDI inputs for industry i, $foward_{it}$ as well as the forward distance statistic, $dist_{ht}$.

3.3 *Variable construction and summary statistics*

Among the collected data, FDI firms are defined as firms with their capital share from foreign countries and Hong Kong, Macau, and Taiwan at no less than 10%, and other firms are domestic firms. To estimate the benchmark regression Eq. (8), we need to construct measures for firm-level productivity, upstream FDI intermediate input shares (for the general productivity-enhancing effect), and the forward distance statistic (for the proximity effect). We estimate firm-level productivity by employing the Ackerberg, Caves, and Frazer (2015) method, which considers the effect of the technology parameter on firms' choice of labor and capital. Specifically we estimate the production function for each 2-digit manufacturing industry using the value-added output. Additional details are in online Appendix C. Then, we follow Eq. (5) to calculate the upstream FDI intermediate input share, where the input-output matrix data are from *China Statistical Yearbook*.

For the firm-level accessibility to upstream FDI firms, we compute the forward distance statistic defined in Eq. (7) as shown in Figure 3. Note that we need to calculate the forward distance statistic for each domestic firm and not for each region, and the large volume of calculations is able to identify the heterogenous productivity spillovers at the firm level. A location is uniquely identified by a 6-digit district code that reflects three tiers of administrative areas in China, with the first two digits referring to the province, the middle two digits referring to the city, and the last two digits referring to the district.[17] Employing Google Maps, we collect the information on longitude and latitude for each district code and then calculate the great circle distance between any two locations.[18]

[Insert Figure 3 here]

We also include major control variables and instrumental variables. At the industry-year level, we include the horizontal and backward spillover channels initiated from Javorcik (2004). The horizontal channel is defined as the ratio of FDI firms' domestic sales over the total domestic sales in the firm's own industry. The backward channel if defined as a weighted sales ratio of FDI firms in all downstream industries of the firm, where the weights are from the input-output matrix. We also incorporate the upstream aggregate domestic productivity and the Herfindahl-Hirschman Index (HHI). We relax the simplifying assumption in the model that only upstream FDI firms generate productivity spillovers and employ the upstream aggregate domestic productivity to control for the impact from upstream domestic firms. We calculate the upstream aggregate domestic productivity as the weighted sum of all upstream domestic firms for each two-digit industry and then take the

[17] The National Bureau of Statistics of China provides a complete list of district codes. The district code is different from the postal code because one location may correspond to multiple postal codes.

[18] We apply the haversine formula to calculate the great circle distance.

log of it, where the weight consists of the input usage shares from China's input-output table and domestic firms' domestic sale share. The HHI is defined as the sum of the top fifty firms' squared market share in each industry. At the province-year level, the real GDP, real imports, and real exports are used to control for provincial economic growth and openness. At the firm level, we incorporate firm age and ownership. Finally, we report the summary statistics of two instruments: the forward FDI policy index and the forward policy weighted distance.

[Insert Table 1 here]

We present the summary statistics of the key variables in Table 1. Panel A summarizes the dependent and independent variables for domestic firms between 2000 and 2007. The dependent variable logged firm-level TFP has a mean of 3.317 with a standard deviation 1.407. The average upstream FDI input share is 15.27 percentage points. Note that according to Eq. (7), *Forward distance* is a double weighted average of a domestic firm's distances to its upstream FDI firms, where the sum of the weights is far below 1. Consequently a domestic firm's weighted average distance to its upstream FDI inputs is relatively small at 146.64 km. Panel B and Panel C report other major control variables. The mean of HHI indicates that China on average has a relatively competitive domestic market. The comparison among the real GDP, real imports, and real exports at the province level shows that China has been opening to trade between 2000 and 2007. Among Chinese domestic firms, 38% are state-owned or collectively owned enterprises, 31% have mixed ownership, and the remaining 31% are privately owned. In the empirical analysis, we use the firms with private ownership as the reference group. In addition, the average age of a domestic firm is a little above 13 years. The instrument forward FDI policy has a mean of 2.22 and a standard deviation of 0.57, indicating the dispersion of FDI encouraging policy cross industries and time. The instrument forward policy weighted distance has a comparable ratio of mean over standard deviation with the forward distance.

Figure 4 illustrates the relationship between the firm-level productivity and the average distance to upstream FDI firms. We categorize all domestic firms into 10 productivity deciles with group 1 least productive and group 10 most productive. Then, we depict *Forward distance* within each productivity decile. The decreasing trend of the average distance to upstream FDI firms from least to most productive domestic firm groups provides the supporting evidence on our major hypothesis that productivity spillovers from upstream FDI firms are mitigated if a domestic firm is geographically more remote from its FDI input suppliers.

[Insert Figure 4 here]

4 Results

In this section, we first present two sets of benchmark results that employ the fixed effects panel regressions and instrumental variable regressions and further consider various robustness checks. All results support the main hypothesis that the positive productivity spillovers from upstream FDI firms are weakened by the geographic remoteness from upstream FDI firms.

4.1 *Benchmark results: Fixed effects regressions with forward distance statistic*

To address the unobserved firm-level heterogeneity, we estimate the benchmark model Eq. (8) by employing the fixed effects panel regressions. In addition to firm, time and industry fixed effects[19], we control for the horizontal and backward spillover channels to distinguish the forward effect, and incorporate the Herfindahl-Hirschman Index to control for industry concentration ratio. We also relax the simplifying assumption of homogenous domestic inputs in the model by including the aggregate upstream domestic productivity. Following Sun et al. (2002) and Chen and Moore (2010), we control the real GDP for market capacity, the amount of road per km^2 for infrastructure development, the number of scientists per thousand persons for research intensity, and the real imports and real exports for openness at the province-time level. Firm-time-level controls include

[19]Because some firms switched their primary industry, we need to control for industry fixed effects.

firm age and firm ownership (state and collective ownership and mixed ownership, with private ownership as the benchmark).

The first two specifications in Table 2 present the results including all domestic firms in China. Column (1) shows with the general productivity-enhancing effect only and column (2) displays the estimation result with the general productivity-enhancing effect and the proximity effect. We take the logarithm of the distance statistic to estimate the effect of the percentage change in distance toward productivity spillovers. We further investigate whether a domestic firm's access to upstream FDI firms has heterogeneous impacts on its productivity because of the unbalanced regional economic development. We categorize firm locations into three economic regions: eastern, middle, and western.[20] The eastern region has embraced greater openness to the world and experienced faster growth, while the middle and western regions, due to their geographic disadvantages and historical conservativeness, have grown relatively slowly. Because of the differentiated regional development across China, domestic firms may have different capacities to absorb advanced technologies; therefore, the knowledge transfers through intermediate inputs may also be different. Specifications (3) to (5) report the results from these three regional subsamples.

[Insert Table 2 here]

Consistent with our model predictions, the coefficients of $Forward$ and $ln(Forward\ distance)$ indicate that an increase in the contribution of upstream FDI generates positive productivity spillovers (general productivity-enhancing effect), and the effect is mitigated if a domestic firm is geographically remoter to its upstream FDI firms (proximity effect). From column (2) of Table 2, if a firm's upstream FDI input share is 1 percentage point higher, its productivity is 2.02% higher. If this firm is 10% geographically more remote to its upstream FDI firms, its productivity is on av-

[20]The eastern region includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; the middle region includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and the western region includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Gansu, Shaanxi, Qinghai, Ningxia, and Xinjiang.

erage 0.59% lower, and the estimate is comparable to that of Keller (2002).[21] With the positive general productivity-enhancing effect and the negative proximity effect together, the productivity spillover effects at the mean levels of forward share and forward distance are positive. Specifically, if other factors remain unchanged, then the marginal productivity spillover at the mean forward share (15.274%) and mean forward distance (146.643km) is 0.013.[22] Also note that if FDI inputs can be acquired at a distance of zero, the proximity effect degenerates and the coefficient for the forward share becomes the average effect of the change in the FDI input share as in Javorcik (2004). Columns (3) to (5) show that the results for different regions are qualitatively consistent with the benchmark full-sample results.

4.2 *Benchmark results: Fixed effects regressions with instrumental variables*

Two criteria for the instrumental variable Before running the instrumental variable regressions, we first check whether the forward policy weighted distance $dist^p_{ht}$ satisfy two criteria: the relevance condition that $dist^p_{ht}$ has good explanatory power and the exclusion condition that the instrument does not affect domestic firms' productivity through other channels. For the relevance condition, given that the forward FDI policy index PC_{jct} positively affects FDI firms' entry and sales as in Figure 2, PE_{ict}, the weighted sum of all upstream FDI policy indexes, should also affect upstream FDI inflow. Panel A of Table 3 shows that PE_{ict} indeed positively affects the city-industry level upstream FDI sales weight W_{ict}, where $W_{ict} \equiv \sum_j \alpha_{ji} \sum_{f\in\Omega_{jt}, f\in c} \tilde{\omega}_{ft}$ with $\tilde{\omega}_{ft} \equiv \frac{fshare_{ft}\cdot\left(Y_{ft}-EX_{ft}\right)}{\sum_{f\in j}\left(Y_{ft}-EX_{ft}\right)}$ representing a FDI firm's domestic sales share.

For the exclusion condition, the policy weighted distance effects of a domestic firms' productivity are only obtained through the channel of upstream FDI firms. The exclusion condition may not hold if the forward policy index PE_{ict} is correlated with the initial city characteristics that may either affect the domestic firms' future productivity growth path or lead to a preferable FDI policy.

[21] Keller (2002) estimates the elasticity of productivity with respect to distance is -0.015.

[22] Similar positive spillover effect is observed at the median levels of forward share (14.871%) and forward distance (128.178km): the marginal productivity spillover is 0.013.

To examine the relationship between the changes in the forward policy index and the industry-city level features before China' accession to the WTO, we choose the value-added share (value added/total production), capital labor share (fixed assets/labor cost), export share (export/total production), state capital share (state capital/total subscribed capital), and weighted average distance from downstream firms ($\sum_h T_{ch} \sum_j \alpha_{ij}\bar{\omega}_{hj,1998}$)[23] for each industry i within a given city c in 1998.

A high value-added share indicates that the industry in a given city is not resource-driven and may develop rapidly with globalization after China's accession to the WTO. A high capital labor share shows the capital accumulation in a city and helps the city to grow rapidly in the future. A high export share reflects that the export-supporting infrastructure and local policies are well developed and can benefit future firm productivity growth. A high state capital share may indicate low efficiency for an average firm and thus is negatively related to future firm productivity growth. A shorter weighted average distance from downstream firms indicates a larger ex ante potential market for upstream FDI firms and may induce more preferable FDI policies afterwards. After regressing the changes in PE_{ict} with the initial industry-city features, we find that the forward policy index is not correlated with these city-level initial values in Panel B of Table 3. Thus, PE_{ict} does not affect productivity because of its correlation with other impacting factors.

[Insert Table 3 here]

Fixed effect regressions with instrumental variables. Table 4 displays the instrumental variable regression results for all domestic firms. Columns (1) and (2) report the results from the first specification. In the first stage in column (1), we instrument the forward distance statistic with the forward policy weighted distance and find a positive relationship between them. The first-stage result confirms that the change in FDI policy after China's accession to the WTO exogenously af-

[23] T_{ch} is the distance between city c and city h, where downstream firms may be located; α_{ij} is the importance of downstream industry j's purchases of inputs from industry i, which are expressed as a share of industry i's total sales; and $\bar{\omega}_{hj,1998}$ is an aggregate sales weight in the initial year 1998 of firms located in city h and industry j, $\bar{\omega}_{hj,1998} \equiv \frac{\sum_{f\in hj,1998}\left(Y_{ft}-EX_{ft}\right)}{\sum_{f\in h,1998}\left(Y_{ft}-EX_{ft}\right)}$.

fects FDI firms' entries and sales; thus, the forward policy weighted distance has good explanatory power for the forward distance statistic. In the second stage, we employ the predicted distance statistic to reexamine the proximity effect. Column (2) shows that the result is qualitatively consistent with the benchmark but slightly larger in magnitude. If a firm's upstream FDI input share is 1 percentage point larger, then its productivity is 2.34% higher. If a domestic firms is 10% geographically closer to its upstream FDI suppliers, then its productivity is 0.63% higher in the whole sample.

In the second specification, we instrument both the portion of FDI inputs and the forward distance statistic by the forward FDI policy index and the policy weighted distance. Note that we need to employ all exogenous variables including both instruments for each endogenous regressor in the first stage. Columns (3) and (4) in Table 4 report the first stage results. In column (3), in addition to the positive correlation between the forward distance statistic and the forward policy weighted distance, a more favorable forward FDI policy can stimulate more FDI entry and thus reduce the forward distance statistic. In column (4), a more favorable forward FDI policy can increase the share of FDI inputs and the policy weighted distance is negatively associated with the FDI input share. The second stage in column (5) is again consistent with the benchmark results. If the upstream FDI input share is 1 percentage point higher, then a firm's productivity is 2.63% higher. If a domestic firms is 10% geographically closer to its upstream FDI suppliers, then its productivity is 0.53% higher in the whole sample.

[Insert Table 4 here]

4.3 *Robustness checks*

The benchmark results may be biased if we ignore alternative spillover channels and incorrectly account for all productivity spillovers from FDI firms as occurring through the gravity effect. In this subsection, we control for other possible spillover channels, instrument the forward distance statistic with the forward policy weighted distance as in the first specification of table 4, and find that the benchmark results are robust [24].

[Insert Table 5 here]

Labor market and capital-good market externalities

Ellison et al. (2010) documents that industries may agglomerate because of people. If domestic firms are geographically closer to FDI firms, then these firms are more likely to hire better trained workers from foreign subsidiaries and thus will receive more spillovers (Fosfuri et al., 2001). Another possible mechanism is that workers may be willing to accept relatively lower wages in the locations where a larger number of firms provide similar job opportunities because they find it easier to be reemployed after quitting their current jobs. Both mechanisms help to reduce the average production cost and improve firm-level productivity. We then need to control for the labor market externality in the benchmark regressions.

Following Alfaro and Chen (2014), we calculate the likelihood that workers can find new jobs at the city level. First, we use a 1% mini-census survey in 2005 to calculate the occupation percentage vector for every industry[25]. The employment similarity matrix with each component represents the correlation of two industry-occupation percentage vectors. Second, in a given city, the probability that workers in an industry will be reemployed locally is the weighted sum of employment similarity between the original industry and all other industries, where the weights are the output shares of the industries in this city. Intuitively, if a worker needs to search for a new job, the output share of each industry represents the likelihood that the worker will enter a new industry. The employment similarity between the original and new industry serves as a proxy for the probability that the worker is able to find a job. Third, we measure the labor market externality as the sum of the probabilities for all industries in the city. Labor market externality is time-varying because the

[24] We also try to control for other possible spillover channels by applying the fixed effects regressions with no instrument and with two instruments, and the results are similar.

[25] Data resource: National Bureau of Statistics.

portions of industry outputs in a given city are changing over time.

Ellison et al. (2010) also documents that industries may agglomerate because of goods. Alfaro and Chen (2014) further point out that firms in a city may be connected through capital goods because better support for their capital goods can be obtained and their investment risk can be reduced through scale economies. Then, we also need to control for the potential capital-good market externality in the robustness check. We first calculate the capital-good usage vector for each industry[26] and then the capital goods similarity matrix. Second, in a given city, the time-varying capital-good market externality is the weighted sum of capital-good similarities between the original industry and all other industries (a proxy for the probability for capital goods to be shared or resold locally), where the weights are the output shares of each industry.

Column (1) in Table 5 presents the results after controlling for both labor market and capital-good market externalities. The coefficients of labor market externality and capital-good market externality are positive, indicating that Chinese domestic firms simultaneously benefit from those externalities. In addition to these channels, the benchmark results are robust, both qualitatively and quantitatively.

Distance to upstream domestic firms

Although we assume homogeneous domestic inputs to simplify the model, in reality, more productive upstream domestic firms are also likely to generate productivity spillovers and the distance to upstream domestic firms affects the overall spillovers. Hence, we calculate the weighted average of the distance to upstream domestic firms for each firm, with the weights reflecting the input-output relationship and upstream domestic firms' market share. Column (2) in Table 5 reports the estimation results that include a firm's distance to upstream domestic firms as an additional control variable. The coefficient for the distance to upstream domestic firms is statistically significant and negative, showing that domestic firms benefit from upstream local suppliers. After controlling the

[26] As the National Bureau of Statistics of China does not provide the use of capital goods (such as computer and machinery) at the industry level, we employ the US capital flow table. For the detailed categories of capital goods, please refer to Alfaro and Chen (2014).

heterogenous domestic forward spillover effect, both the statistical and economic significance of the benchmark results do not change much.

Imported intermediate inputs

Some domestic firms also obtain access to foreign varieties of inputs from importing. In this case, these firms can gain additional technology spillovers from the imported inputs, as found by Halpern et al. (2015) for Hungarian firms. We would like to separate the effect of imported inputs from that of FDI inputs. Applying the method from Yu (2015), we combine our data with the product-level import value from the Chinese customs, Overall, 66% of foreign firms and 12.5% of domestic firms import inputs. We then control the imported input ratio in the benchmark regressions, and the estimation results are shown in Column (3) of Table 5. Different from Halpern et al. (2015), imported inputs do not benefit Chinese firms in their productivity, which is likely to be caused by the large proportion of processing trade in China, as in Yu (2015). However, the general productivity-enhancing effect and the proximity effect from FDI inputs are robust in both statistical significance and economic magnitude.

Firms that entered the market before 2000

While we have controlled for FDI firms' endogenous location choice, domestic firms may also choose to enter the locations where more upstream FDI firms are located and then receive more productivity spillovers. To deal with the possible endogenous problem of domestic firms, we focus on the sub-sample of domestic firms that have entered before 2000. These firms chose their location before China's accession to the WTO and thus did not target the locations where FDI firms flowed in later. Column (4) of Table 5 displays the results. Again, we find that the general productivity-enhancing effect exists for these continuing domestic firms. However, the proximity effect is no longer significant and has a much smaller magnitude; thus, it is likely that older and more established domestic Chinese firms do not suffer much from the negative proximity effect.

5 Conclusion

This paper quantifies the heterogeneous FDI forward productivity spillovers at the firm level. Focusing on the channel of FDI inputs, we identify the gravity effect in productivity spillovers both theoretically and empirically. The relative contribution of FDI inputs in upstream industries generates a positive productivity spillover to the downstream domestic firms. Meanwhile, the positive spillover effect is weakened by the distance between a domestic firm and its upstream FDI suppliers. These findings further suggest that if policymakers want domestic firms to absorb productivity spillovers more efficiently, they need to design more precise stimulating policies according to domestic firms' differentiated access to FDI inputs. Examples of these policies include reducing FDI input procurement costs for domestic firms and encouraging multinational firms to build affiliates in regions where FDI inflows are deficient but domestic firms need inputs from upstream FDI firms. These policies will facilitate domestic firms in absorbing productivity spillovers and will ultimately help to achieve balanced regional economic growth.

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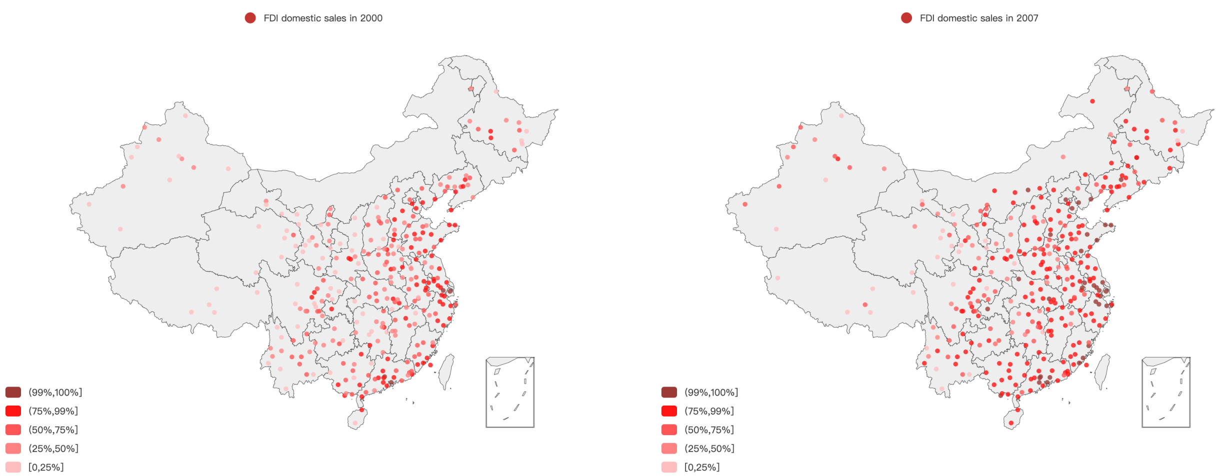

Fig. 1: Domestic Sales of FDI Firms in 2000 and 2007

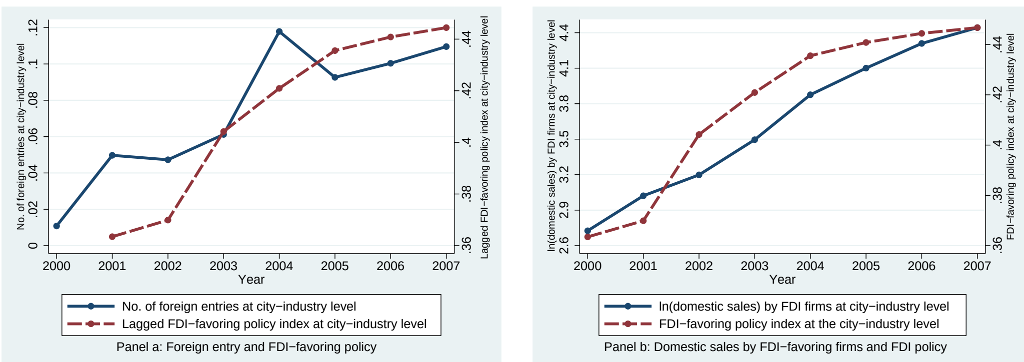

Fig. 2: Entry and Domestic Sales of FDI Firms and FDI Policy

$$dist_{ht} = \sum_j \alpha_{ji} \left(\sum_{f \in \Omega_{jt}} \frac{fshare_{ft} \, (Y_{ft} - EX_{ft})}{\sum_{f \in j} (Y_{ft} - EX_{ft})} T_{fh} \right)$$

Sum the average distances to all upstream industries with weights α_{ji}

$$\sum_{f \in \Omega_{jt}} \frac{fshare_{ft} \, (Y_{ft} - EX_{ft})}{\sum_{f \in j} (Y_{ft} - EX_{ft})} T_{fh}$$

Take the weighted average of all distances to FDI firms in upstream industry *j* in year *t*

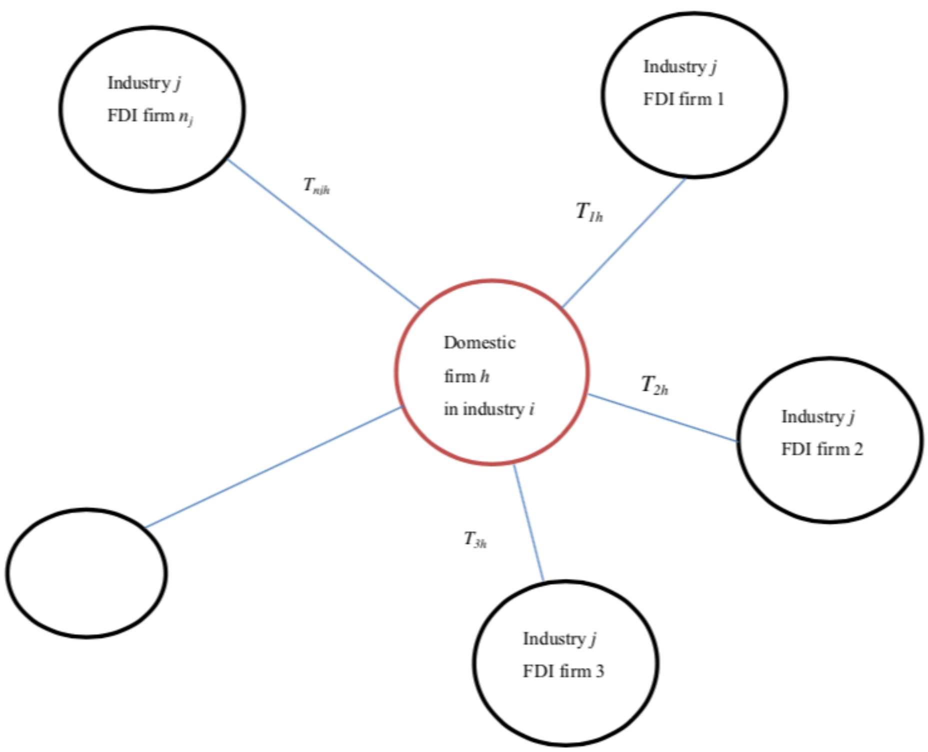

Fig. 3: Firm Distance Distributions

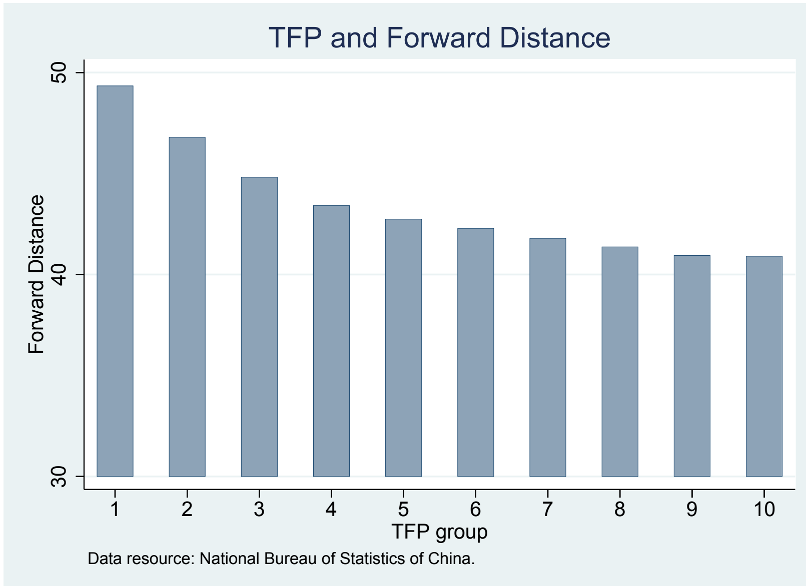

Fig. 4: Productivity and Distance Statistic

Note: TFP groups 1 to 10 include the least to most productive domestic firms between 2000 and 2007. The distance statistic is the weighted mean distance between a domestic firm and its upstream FDI suppliers.

Table 1: Summary Statistics

Panel A: Dependent and Key Independent Variables

Variables	No. of Obs.	Mean	Std. Dev.
ln(TFP)	611,248	3.317	1.407
Forward (%)	611,248	15.274	6.266
Forward distance (km)	611,248	146.643	83.126

Panel B: Control Variables

Variables	No. of Obs.	Mean	Std. Dev.
Horizontal (%)	611,248	29.272	12.766
Backwrd (%)	611,248	20.347	10.376
Upstream aggregate domestic productivity	611,248	1.763	0.490
HHI	611,248	275.187	432.591
Real GDP (b. CNY)	611,248	893.535	645.535
Road per km^2 (km)	611,248	0.624	0.361
No. of R&D scientists per thousand persons	611,248	38.548	36.222
Real Imports (b. CNY)	611,248	311.593	457.044
Real Exports (b. CNY)	611,248	378.097	571.129
Firm age	611,248	13.227	13.938
State and Collective ownership	611,248	0.382	0.486
Mixed ownership	611,248	0.313	0.464

Panel C: Instrumental Variables

Variables	No. of Obs.	Mean	Std. Dev.
Forward FDI policy	611,248	2.220	0.573
Forward policy weighted distance (km)	611,248	602.825	245.969

Note: ln(TFP) is firm-level measured productivity. Forward is the portion of domestic sales contributed by upstream FDI firms. Forward distance refers to a local firm's weighted average distance to its upstream FDI firms. Horizontal is a measure of the weighted average foreign capital contribution in sales in the local firm's industry. Backward is a measure of the extent of foreign capital contribution in sales from all downstream industries of the firm. Upstream aggregate domestic productivity is the weighted average productivity of all domestic firms from the upstream industries for the local firm. The HHI is defined as the sum of top fifty firms' squared market share in each 4-digit industry. Real GDP, real imports and real exports are at the province-time level (2000 as the base year). State and collective ownership defines firms that are owned by the state or by members of an institution. Mixed ownership defines firms that are owned by the state, a collective, a private entity, or other entities through the stockholding. Forward FDI policy is defined as a weighted sum of upstream FDI policies for a given industry, with weights from the input-output matrix. Forward policy weighted distance is defined as the FDI policy weighted average distance toward upstream FDI firms for a given firm.

Table 2: Benchmark Results

Fixed effects panel regressions

Dependent variable: ln(TFP)	All Regions (1)	All Regions (2)	Eastern China (3)	Middle China (4)	Western China (5)
Forward	0.0174^{***}	0.0202^{***}	0.0121^{***}	0.0178^{***}	0.0213^{***}
	(0.0018)	(0.0015)	(0.0028)	(0.0029)	(0.0024)
ln(Forward distance)		-0.0592^{***}	-0.0714^{***}	-0.0467^{***}	-0.0203
		(0.0009)	(0.0127)	(0.0166)	(0.0196)
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	611,248	611,248	394,082	143,245	73,921
No. of firms	239,110	239,110	157,511	56,123	25,481
R^2	0.3077	0.3086	0.2772	0.3495	0.3095

Note: (1) All variable definitions are in Table 1. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. (2) Other control variables include the upstream horizontal channel, backward channel, upstream aggregate domestic productivity and HHI at the industry-time level, real GDP, road per km^2, number of R&D scientists per thousand persons, real exports at the province-time level, and firm age and firm ownership at the firm-time level. We control the industry fixed effects in addition to firm fixed effects because a few firms switched their primary industries. (3) Eastern China area includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; middle China area includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; and western China area includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Gansu, Shaanxi, Qinghai, Ningxia, and Xinjiang. The sum of the number of firms of different regions exceeds the total number of firms because a few firms change regions over time.

Table 3: Relevance and Exclusion Conditions of the Instrument Variable

Panel A: Forward FDI Policy and FDI Input Sales Weight
Fixed effects panel regressions

Dependent variable: Upstream FDI sales weight (W_{ict})	All Regions (1)
Forward FDI Policy Index (PE_{ict})	0.0546^{***}
	(0.0115)
Time fixed effect	Yes
No. of obs.	87,840
No. of industry-city pairs	10,980
R^2	0.1987

Note: Robust standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Panel B: Correlation Analysis between Forward FDI Policy and Initial city-industry Features

Dependent variable:	$\%\Delta PE_{ict}$ (1)	$\%\Delta PE_{ic}$ (2)
Value added share$_{ic1998}$	-0.329	-0.051
	(0.312)	(0.032)
Capital labor ratio$_{ic1998}$	-0.277	0.011
	(0.208)	(0.008)
Export share$_{ic1998}$	2.889	1.097
	(1.855)	(0.611)
State capital share$_{ic1998}$	-1.090	0.513
	(3.219)	(0.537)
ln(weighted distance to downstream firms)$_{ic1998}$	-1.278	0.054
	(1.121)	(0.320)
No. of obs.	48,677	7.060
R-squared	0.0002	0.0005

Note: (1) Column (1) uses the $\%\Delta PE_{ict} = \frac{(PE_{ict} - PE_{ict-1})}{PE_{ict}}$. Column (2) uses the $\%\Delta PE_{ic} = \frac{(PE_{ic2005} - PE_{ic2000})}{PE_{ic2000}}$ since year 2005 shows the biggest change of the forward FDI policy in our data. (2) Robust standard errors are clustered at city-industry level and presented in parentheses.

Table 4: Benchmark Results: Endogenous Location Choice

Two-stage fixed effects panel regressions

	IV on Forward distance		IV on Forward and Forward distance		
	1st stage	2nd stage	1st stage		2nd stage
Dependent variable:	ln(Forward distance)	ln(TFP)	ln(Forward distance)	Forward	ln(TFP)
	(1)	(2)	(3)	(4)	(5)
Forward		0.0234^{***}			
		(0.0018)			
$\hat{Forward}$					0.0263^{***}
					(0.0020)
$ln(\hat{Forward\ distance})$		-0.0630^{***}			-0.0534^{***}
		(0.0187)			(0.0190)
ln (Forward policy weighted distance)	0.1089^{***}		0.1228^{***}	-1.9477^{***}	
	(0.0104)		(0.0123)	(0.1170)	
Forward FDI policy			-0.0250^{**}	2.2502^{***}	
			(0.0103)	(0.0503)	
Firm fixed effect	Yes	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes	Yes
No. of obs.	611,248	611,248	611,248	611,248	611,248
No. of firms	239,110	239,110	239,110	239,110	239,110
R^2		0.2895			0.2463
Weak instrument test					
Anderson-Rubin Wald test	33.97^{***}		334.38^{***}		
Stock-Wright LM S statistic	34.13^{***}		345.61^{***}		
Cragg-Donald Wald F statistic	3735.26^{***}		2011.64^{***}		

Note: (1) In the first specification, ln(Forward distance) is instrumented by ln(Forward policy weighted distance) defined in section 3.2. In the second specification, Forward and ln(Forward distance) are instrumented by the forward FDI policy index and ln(forward policy weighted distance) jointly. All other variables are defined in Tables 1 and 2. (2) Robust standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 5: Robustness Checks

Two-stage fixed effects panel regressions

Dependent variable: ln(TFP)	L&K market externalities (1)	Distance to upstream domestic firms (2)	Imported inputs ratio (3)	Startyear < 2000 (4)
Forward	0.0170^{***}	0.0157^{***}	0.0172^{***}	0.0175^{***}
	(0.0031)	(0.0032)	(0.0031)	(0.0042)
$ln(Forw\hat{ar}d\ distance)$	-0.0648^{***}	-0.0640^{***}	-0.0628^{***}	-0.0217
	(0.0186)	(0.0186)	(0.0186)	(0.0310)
Labor market externality	0.1373^{***}			
	(0.0464)			
K-good market externality	0.1008^{***}			
	(0.0738)			
Distance to upstream domestic firms		-0.1372^{***}		
		(0.0591)		
Imported Input Ratio			-0.8223^{***}	
			(0.2681)	
Firm fixed effect	Yes	Yes	Yes	Yes
Time fixed effect	Yes	Yes	Yes	Yes
Industry fixed effect	Yes	Yes	Yes	Yes
Other controls	Yes	Yes	Yes	Yes
No. of obs.	611,248	611,248	611,248	423,585
No. of firms	239,110	239,110	239,110	149,342
R^2	0.2903	0.2982	0.2907	0.2856

Note: (1) In the first stage, ln(Forward distance) is instrumented by ln(Forward policy weighted distance), which is defined in section 3.2. (2) All variable definitions are in Tables 1 and 2. Standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively. (3) Labor market externality refers to the probability that a worker can be reallocated to a position within a city. Capital-good market externality refers to the probability that equipment can be resold within a city. (4) Distance to upstream domestic firms is the log value of the weighted average distance to all domestic inputs suppliers. (5) Imported input ratio is the total value of imported products over that of production.

Online Appendix A

Cost minimization

The price for FDI input demand X_{Fjh} is

$$P_{Fjh} = P_{Fj}\big[\sum_{f\in\Omega_j}\omega_f P(T_{fh})^{1-\theta}\big]^{\frac{1}{1-\theta}} = P_{Fj}G_{jh},$$

where $G_{jh} \equiv \big[\sum_{f\in\Omega_j}\omega_f P(T_{fh})^{1-\theta}\big]^{1/(1-\theta)}$.

If the industry price index is $P_j \equiv \big(P_{Dj}\big)^{1-\kappa_j}\big(P_{Fj}\big)^{\kappa_j}$, then the price index for inputs from industry j is

$$P_{jh} = \big(P_{Dj}\big)^{1-\kappa_j}\big(\eta\big)^{-\kappa_j}\big(P_{Fj}G_{jh}\big)^{\kappa_j} = P_j\big(\eta\big)^{-\kappa_j}\big(G_{jh}\big)^{\kappa_j}.$$

We then rewrite the input demand of firm h based on its input expenditure M_h and price index P_h^x:

$$X_h = M_h/P_h^x = M_h\prod_j\big(P_j\big)^{-\alpha_{ji}}\prod_j\big(\eta^{\kappa_j}\big)^{\alpha_{ji}}\prod_j\big((G_{jh})^{-\kappa_j}\big)^{\alpha_{ji}}.$$

Given $P(T_{fh}) = \big(C-T_{fh}\big)^{1/(1-\theta)}$, the last item in the logged input demand becomes as follows:

$$lnG_{jh} = ln\big[\sum_f\omega_f P(T_{fh})^{1-\theta}\big]^{\frac{1}{1-\theta}} = -\frac{1}{\theta-1}ln\big[\sum_f\omega_f\big(C-T_{fh}\big)\big] \doteq -\frac{1}{\theta-1}\big[C-\sum_f\omega_f T_{fh}-1\big],$$

where the last approximation employs the Taylor expansion and $\sum_f\omega_f = 1$. Note that we need $C-\sum_f\omega_f T_{fh}\in(0,2]$ for Taylor expansion. We also need $C > max_f T_{fh}$ to guarantee that trade cost $P(T_{fh}) > 0$. In summary, we set the constant C as $\sum_f\omega_f T_{fh} < C \leq \sum_f\omega_f T_{fh}+2$.

Taking logs of the input demand and ignoring the constants, we obtain the following:

$$x_h = m_h - \sum_j \alpha_{ji} p_j + ln\eta \sum_j \alpha_{ji} \kappa_j - \frac{1}{\theta - 1} \sum_j \alpha_{ji} \kappa_j \sum_f \omega_f T_{fh},$$

where the lower case letters indicate the logged variables.

Online Appendix B

Domestic and FDI inputs: The CES function

In the benchmark model, the demand of firm h for domestic and FDI inputs in industry j, X_{Djh} and X_{Fjh} is a Cobb-Douglas function. In this appendix, we show that if we set the demand for industry j as a CES function with the elasticity of substitution $\zeta(\zeta > 1)$, all qualitative results hold. Specifically, the input demand in industry j is as follows:

$$X_{jh} = \left[(X_{Djh})^{\frac{\zeta-1}{\zeta}} + (\eta X_{Fjh})^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}}.$$

When solving the price index P_{jh} for the input demand X_{jh}, we employ $P_{Djh} = P_{Dj}$, $P_{Fjh} = P_{Fj}G_{jh}$, and $G_{jh} \equiv \left[\sum_{f\in\Omega_j} \omega_f P(T_{fh})^{1-\theta}\right]^{1/(1-\theta)}$ in the benchmark model to generate the following:

$$P_{jh} = \left[(P_{Djh})^{1-\zeta} + (P_{Fjh}/\eta)^{1-\zeta}\right]^{\frac{1}{1-\zeta}} = \left[(P_{Dj})^{1-\zeta} + (P_{Fj}/\eta)^{1-\zeta}(G_{jh})^{1-\zeta}\right]^{\frac{1}{1-\zeta}}.$$

We further follow Halpern et al. (2015) to denote $B_j = \eta P_{Dj}/P_{Fj}$ as the FDI input gain and simplify the price index as follows:

$$P_{jh} = P_{Dj}\left[1 + (B_j)^{\zeta-1}(G_{jh})^{1-\zeta}\right]^{\frac{1}{1-\zeta}}.$$

Then, the price index for the input demand from all industries is as follows:

$$P_h^x = \prod_j \left(P_{jh}\right)^{\alpha_{ji}} = \prod_j \left(P_{Dj}\right)^{\alpha_{ji}} \prod_j \{[1 + (B_j)^{\zeta-1}(G_{jh})^{1-\zeta}]^{\frac{1}{1-\zeta}}\}^{\alpha_{ji}}.$$

Rewriting the input demand of firm h based on its input expenditure and price and taking its logarithm yields the following:

$$X_h = M_h/P_h^x = M_h \prod_j \left(P_{Dj}\right)^{-\alpha_{ji}} \prod_j \{[1 + (B_j)^{\zeta-1}(G_{jh})^{1-\zeta}]^{\frac{1}{1-\zeta}}\}^{-\alpha_{ji}},$$
$$x_h = m_h - \sum_j \alpha_{ji} p_{Dj} - \sum_j \alpha_{ji} \frac{1}{1-\zeta} ln[1 + (B_j/G_{jh})^{\zeta-1}].$$

Note that if $B_j/G_{jh} >> 1$ (this condition can be achieved if the constant C in G_{jh} is large), then $ln[1 + (B_j/G_{jh})^{\zeta-1}] \doteq ln(B_j/G_{jh})^{\zeta-1}$. As in Appendix A, the firm-specific access toward upstream FDI suppliers can be approximated as $lnG_{jh} \doteq -\frac{1}{\theta-1}\left[C - \sum_f \omega_f T_{fh} - 1\right]$. Then, after ignoring the constant, the logarithm of input demand becomes as follows:

$$x_h = m_h - \sum_j \alpha_{ji} p_{Dj} + \sum_j \alpha_{ji} lnB_j - \frac{1}{\theta-1} \sum_j \alpha_{ji} \sum_f \omega_f T_{fh}.$$

Then, the alternative model also generates industry-level effect $\sum_j \alpha_{ji} lnB_j$ and firm-specific effect $-\frac{1}{\theta-1}\sum_j \alpha_{ji} \sum_f \omega_f T_{fh}$.

Online Appendix C

We estimate firm productivity within each 2-digit industry. Assume the production function of a firm is the Cobb-Douglas function. Specifically, the production function of firm h in industry i is as follows:

$$y_{hit}^{va} = \gamma_k k_{hit} + \gamma_l l_{hit} + a_{hit} + \epsilon_{hit}, \tag{C1}$$

where y, k and l stand for the logarithm of value-added real output[27], capital stock and total employment; a denotes the technology parameter, ϵ is the residual; subscripts h, i and t stand for firm, industry and time, respectively; and γ_k and γ_l, which are the coefficients to be estimated, are capital and labor shares of output in industry i, respectively. The real value added is deflated by the industry price index because we assume that the output market is perfectly competitive and all firms charge a homogeneous price. Assume that the productivity a_{hit} evolves according to a first-order Markov process:

$$a_{hit} = E[a_{hit}|I_{hit-1}] + \xi_{hit} = E[a_{hit}|a_{hit-1}] + \xi_{hit},$$

where I_{hit-1} is the information available in period $t-1$ and ξ_{hit} is the innovation of productivity at t and represents mean independent of I_{hit-1}.

The estimation procedure consists of three steps. The first step isolates all firms in industry i from the whole data to controls for industry-level differences in output, capital and labor, and the capital and labor share of output; the second step separates a_{hit} from ϵ_{hit}; and the third step estimates γ_k and γ_l.

The first step does not require additional explanation. In the second step, assume the firm

[27] Due to the Cobb-Douglas production structure, the expenditure ratio of intermediate inputs is $M_{hit}/\big(P_{it}Y_{hit}\big) = \gamma_x$. We estimate γ_x as the cost share of intermediate inputs in industry i. Then, the value added output is $P_{it}Y_{hit}^{va} = (1-\hat{\gamma}_x)P_{it}Y_{hit}$ or $Y_{hit}^{va} = (1-\hat{\gamma}_x)Y_{hit}$.

chooses k_{hit} and l_{hit} in period $t-1$ and the real intermediate input m^r_{hit} in period t. We write the choice of the intermediate input as follows:

$$m^r_{hit} = f_t(k_{hit}, l_{hit}, a_{hit}). \tag{C2}$$

Substituting (C2) to (C1) yields

$$y^{va}_{hit} = \gamma_k k_{hit} + \gamma_l l_{hit} + f_t^{-1}(k_{hit}, l_{hit}, m^r_{hit}) + \epsilon_{hit}. \tag{C3}$$

We cannot identify γ_k and γ_l but can obtain an estimate $\hat{\Phi}_{hit}$ or the predicted value of y^{va}_{hit}, where

$$\hat{\Phi}_t(k_{hit}, l_{hit}, m^r_{hit}) = \gamma_k k_{hit} + \gamma_l l_{hit} + f_t^{-1}(k_{hit}, l_{hit}, m^r_{hit}).$$

Therefore, $\hat{\Phi}_{hit}$ separates a_{hit} from ϵ_{hit}.

In the third step, we find two independent moment conditions to identify γ_k and γ_l. First, if both k_{hit} and l_{hit} are determined one period ahead and hence $k_{hit}, l_{hit} \in I_{hit-1}$, they should be independent of the productivity innovation ξ_{hit}, i.e., $E[\xi_{hit}|k_{hit}] = 0$ and $E[\xi_{hit}|l_{hit}] = 0$. In summary, two conditions imply the following:

$$E[\xi_{hit} \begin{pmatrix} k_{hit} \\ l_{hit} \end{pmatrix}] = 0. \tag{C4}$$

We then estimate γ_k and γ_l by employing these two moment conditions in (C4). Specifically, (i) given a candidate value of (γ_k, γ_l), the corresponding $a_{hit}(\gamma_k, \gamma_l)$ is $a_{hit}(\gamma_k, \gamma_l) = \hat{\Phi}_{hit} - \gamma_k k_{hit} - \gamma_l l_{hit}$; (ii) recover $\xi_{hit}(\gamma_k, \gamma_l)$ by regressing a_{hit} on a_{hit-1}; (iii) estimate (γ_k, γ_l) by minimizing the sample analogue of the moment condition (C4):

$$\frac{1}{N_i}\frac{1}{T}\sum_h\sum_t \xi_{hit}(\gamma_k,\gamma_l)\begin{pmatrix} k_{hit} \\ l_{hit} \end{pmatrix},$$

where T and N_i are the number of time periods and the number of firms in industry i, respectively.