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

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Abstract

We distinguish the heterogeneous productivity spillovers from foreign direct investment (FDI) at the firm level. Based on a multi-sector production model, we construct a firm-level distance statistic that measures a domestic firm's accessibility to intermediate inputs produced by upstream FDI firms. We then estimate the gravity of intermediate inputs—a domestic firm enjoys a higher productivity if it gains access to more inputs sold by FDI firms (general productivity-enhancing effect) and it is geographically closer to upstream FDI firms (proximity effect). Using the Chinese firm data between 2000 and 2007, we exploit the FDI-encouraging policy shock that changes upstream FDI firms' entry, exit, and market share, and thus affects the firm-level distance statistic exogenously. We find empirical supports that (i) if a domestic firm's FDI input share increases by 1 percentage point, its productivity increases by 2.15%, and (ii) if this firm is 10% geographically remoter than an otherwise identical firm to upstream FDI firms, its productivity is 1.42% lower.

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

Keywords: FDI, forward productivity spillover, gravity effect, China

1 Introduction

Foreign direct investment (FDI) has been surging into developing countries and emerging markets since the 1990s. Take China as an example, foreign capital in the manufacturing sector has more than tripled between 2000 and 2007, as shown in Figure 1. Facing the large inflow of FDI, a natural question arises—does doing business with FDI firms increase domestic firms' productivity? If so, how does the positive externality from FDI firms transfer to domestic firms? An ideal way to explore the channel of productivity spillover is to examine the business-to-business transactions between foreign subsidiaries and domestic firms. However, the firm-level transaction data are difficult to find. Consequently, in order to identify the productivity spillovers, the mainstream research relies on the time variation in FDI inflow that is identical to all firms in a specific industry.[1] Even though the previous literature identifies the average effect of FDI on domestic firms at the industry level, it is unclear whether the spillover effect is heterogenous across individual firms, or how to quantify the difference in spillovers between them.

This paper aims to examine the channels of productivity spillovers at the firm level. We first create a novel firm-level distance statistic between upstream FDI firms and downstream domestic firms. Then we exploit the FDI-encouraging shock that affects a firm's distance statistic exogenously by changing upstream FDI firms' entry, exit, and market share, and quantify how the distance statistic may obstruct upstream productivity spillovers in a Chinese firm-level dataset. The estimation helps us to understand the heterogeneity of FDI spillovers at the firm level, besides the average forward spillovers identical to all firms in a given industry.[2] Second, the estimated effect of firms' geographic access to FDI inputs on productivity spillovers adds to a trend of liter-

[1] See Javorcik (2004) and Liu (2008) on the channel of the same, upstream, and downstream industries. Haddad and Harrison (1993), Hale and Long (2011), Fons-Rosen, Kalemli-Ozcan, Sorensen, Villegas-Sanchez, and Volosovych (2013), and Gorodnichenko, Svejnar, and Terrell (2014) find mixed evidence of positive productivity spillovers from FDI firms. Also see Aitken and Harrison (1999) and Harrison, Love, and McMillan (2004) on the channel of financing; Fosfuri, Motta, and Ronde (2001) and Glass and Saggi (2002) on the channel of workers' mobility.

[2] See Liu, Wang, and Wei (2009), Lin, Liu, and Zhang (2009), Wang (2010), and Xu and Sheng (2012) for the forward channel in China.

ature that discusses how the geographical remoteness impedes technology diffusion at the country level (Keller, 2002; Blonigen, Davies, Waddell, and Naughton, 2007; Comin, Dmitriev, and Rossi-Hansberg, 2012). Different from Baltagi, Egger, and Kesina (2016) that includes the spatial correlation in the intra-industry spillovers, this paper quantifies the effect of a domestic firm's distance statistic on receiving upstream FDI spillovers. Third, the estimated gravity effect—the access to FDI inputs combined with the geographic closeness to upstream FDI firms—identifies a specific channel of the benefits from the agglomeration across the supply chain (Aitken and Harrison, 1999; Ellison, Glaeser, and Kerr, 2010). In comparison with the agglomeration measure for a region or for an industry, we are able to investigate the firm-level agglomeration effect induced by exogenous policy shocks. Fourth, complementing the literature on the role of imported inputs in enhancing firm-level productivity (Goldberg, Khandelwal, Pavcnik, and Topalova, 2010; Amiti, Itskhoki, and Konings, 2014; and Halpern, Koren, and Szeidl, 2015), this paper shows that the firm-level productivity can be improved if domestic firms employ more FDI inputs, especially in developing countries that have already attracted a large amount of FDI.

In order to identify the firm-level FDI productivity spillovers, we look for some measurable links between upstream FDI firms and downstream domestic firms, through which advanced technology is transferred heterogeneously across domestic firms. Inputs produced by FDI firms and used by domestic firms are one of the ideal candidates, because the advanced technology embodied in FDI products (Keller and Yeaple, 2013) and their high quality can improve domestic firms' productivity. A domestic firm has an easy access to FDI inputs if it is geographically close to upstream FDI firms. Our key identification assumption is that if a country relaxes its FDI restrictions, more FDI flows into the domestic market, and then the entry, exit, and market share change of upstream FDI firms are plausibly exogenous to a specific domestic firm. All those changes of upstream FDI firms alter the distance statistic weighted by input sales between them and the domestic firm, even though a pairwise distance between a FDI firm and the domestic firm is constant over time. Therefore the distance statistic is heterogeneous for domestic firms in the same industry and for the same

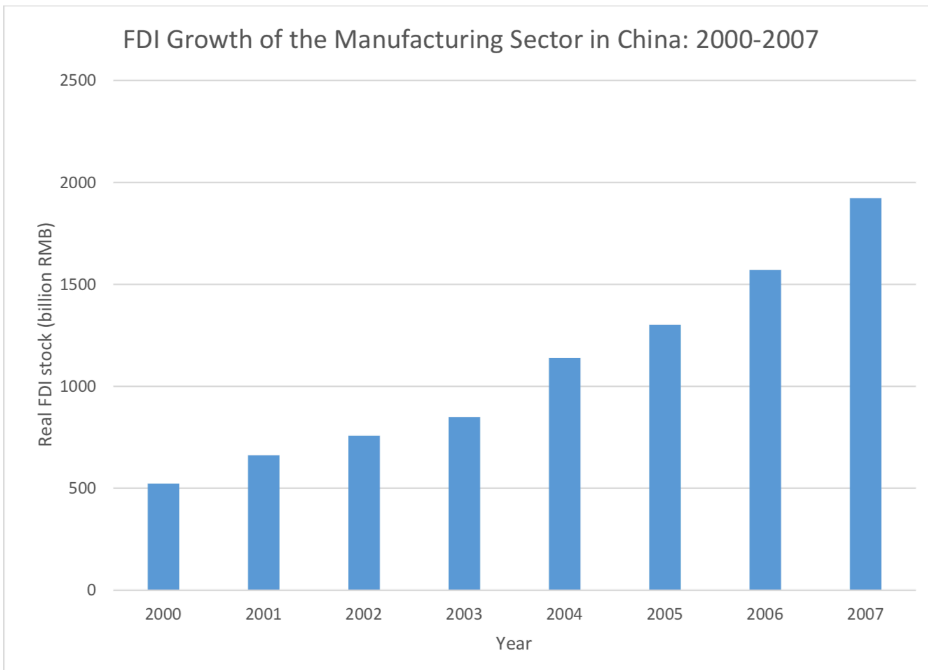

Fig. 1: FDI Growth of the Manufacturing Factor in China

Note: FDI stock of manufacturing firms is calculated as the sum of subscribed capital from Hong Kong, Macau, Taiwan, and foreign countries for all manufacturing firms in Annual Surveys of Industrial Production and is deflated by Production Price Index (base year: 2000).

domestic firm across years. The heterogeneous distance statistic further affects the usage of FDI inputs by domestic firms and thus the productivity spillovers for them.

We formalize the idea as the gravity effect of intermediate inputs—not only the portion of inputs from upstream FDI firms, but also the weighted average geographical distance from upstream FDI firms affects productivity spillovers. In a multi-sector production model, we are able to decompose the measured total factor productivity of a firm into a firm-level technology parameter, a homogeneous productivity-enhancing effect from FDI inputs, and a heterogeneous proximity effect that depends on the distance from its upstream FDI firms. The latter two effects indicate the channels through which a domestic firm absorbs productivity spillovers from its upstream FDI firms.

We employ the Chinese firm-level data from 2000 to 2007 to estimate the gravity effect of FDI inputs in productivity spillovers. Besides the detailed production information of foreign subsidiaries and domestic firms, the time span of the data covers China's accession to the World Trade Organization (WTO) in 2001. The Chinese government relaxed its restrictions on FDI after joining the WTO. A series of policies became effective between 2002 and 2005, encouraging foreign multinational enterprises to enter different industries extensively, to advance into the less developed middle and western regions, and to merge and acquire domestic firms besides greenfield investment. As a result, more FDI firms entered, increased their sales revenue, and reshaped Chinese domestic firms' accessibility to FDI inputs according to their geographic proximity to FDI firms.

We decompose the spillover effect into the general productivity-enhancing effect and the proximity effect. The general productivity-enhancing effect is related to the overall contribution of FDI in domestic firms' input use, and it is homogeneous to all domestic firms in a given downstream industry. Our benchmark results show that if a Chinese domestic firm's FDI input share increases by 1 percentage point, its productivity increases by 2.15%. The proximity effect estimates the heterogeneous spillovers based on the distance statistic between a domestic firm and its upstream FDI firms. We find that if the weighted average distance for a domestic firm is 10% less, it is 1.42% more productive.

Our empirical results are robust after we control for the FDI productivity spillovers from the same and downstream industries, the local labor and capital-good market externalities, the upstream domestic firms' spillovers, and the effects of imported intermediate inputs. We also consider the potential endogeneity problem—if both domestic and FDI firms agglomerate in the locations where only more productive firms are able to survive, our estimates may be biased. In order to overcome the estimation bias, we first focus on a subsample of domestic firms that entered the market before 2000, because these domestic firms' location choices upon entry were not affected by the significant FDI inflow after China's accession to WTO in 2001. As to FDI firms, we estimate the likelihood that FDI firms choose to locate for each district, and control this first-stage probability in the productivity spillover regressions. All results are qualitatively and quantitatively consistent with our benchmark results.

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 preliminary and benchmark results, as well as the robustness checks. Section 5 concludes.

2 Model and Estimation Strategy

In this section, we develop a multi-sector production model with heterogeneous firms. This model allows us to 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 domestic firms' geographical accessibility to upstream FDI firms. The latter two effects will be altered through the entry, exit, and market share changes of upstream FDI firms if a country changes its FDI policy. According to the model, we propose the benchmark estimation equation that identifies these two effects which jointly reveal the gravity of intermediate inputs in productivity spillovers from upstream FDI firms.

2.1 *The 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—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 input of firm h, X_h, is a composite of inputs X_{jh} from upstream industries indexed by j:

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

where α_{ji} is the share of intermediate inputs from upstream industry j, $\sum_j \alpha_{ji} = 1$, and $C_{i1} = \prod_j \alpha_{ji}^{\alpha_{ji}}$.

The intermediate inputs X_{jh} can be further decomposed to two varieties produced by domestic and FDI firms: X_{Djh} and X_{Fjh}, which are imperfect substitutes in a Cobb-Douglas function:

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

where $\kappa_j \in (0,1)$ is the parameter that measures the importance of FDI inputs in industry j. A higher κ_j denotes a growth of upstream FDI market share. C_{i2} is a constant, and $C_{i2} = (1-\kappa_j)^{1-\kappa_j}\kappa_j^{\kappa_j}$. Parameter η measures the productivity-enhancing effect of FDI intermediate inputs, and $\eta > 1$.[3] Intuitively, η is the advantage of spending one unit of expenditure on FDI inputs rather than domestic counterparts. Goldberg et al. (2010), Amiti, et al. (2014), and 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 parameter η represents the effectiveness of FDI inputs—the high quality of FDI inputs, the associated complementary knowledge from using them, and the additional built-in characteristics of FDI inputs amount to improve downstream firms' productivity.

In order to focus on the impacts of FDI intermediate inputs, we assume that inputs from domestic firms are perfect substitutes. The FDI input X_{Fjh} consists of intermediate inputs from upstream FDI firms indexed by f:

$$X_{Fjh} = C_{Fj} \prod_{f \in \Omega_j} \left(e^{-T_{fh}} X_{fh}\right)^{\omega_f},$$

where Ω_j is the set of FDI firms in industry j. Since no firm-level input-output matrix is available in our data, we need to assume that there is no fixed cost to purchase FDI intermediate inputs and therefore a firm can purchase inputs from all upstream FDI firms. T_{fh} is the distance between FDI firm f and domestic firm h. Following Keller (2002) and Ellison et al. (2010), the productivity-enhancing effect of FDI input is weakened if distance T_{fh} is larger, because firm h is more difficult to receive spillovers such as hand-to-hand training, on-time technology support, and complementary services from its input supplier f.[4] ω_f is the share of intermediate inputs sold by FDI firm f,

[3] If $\eta \leq 1$, FDI intermediate inputs generate no productivity-enhancing effect to downstream domestic firms.

[4] To guarantee that FDI inputs have positive spillovers, we can find a constant C_T such that $\eta e^{C_T} \prod_{f \in \Omega_j} \left(e^{-T_{fh}}\right)^{\omega_f} > 1$. Since the constant C_T plays no role in the estimation, we ignore it to make the model concise.

and $\sum_{f\in\Omega_j}\omega_f = 1$. A higher ω_f represents that firm f expands its market share and has a larger impact on firm h. C_{Fj} is a constant, and $C_{Fj} = \prod_{f\in\Omega_j}\omega_f^{\omega_f}$.

The intermediate input expenditure and production. Firm h minimizes its expenditure M_h on intermediate inputs X_h. Given that both domestic and FDI firms in industry j sell inputs at P_j, the price index for industry-j FDI intermediate inputs is

$$P_{Fjh} = P_j G_{jh}, \;\; G_{jh} \equiv \prod_{f\in\Omega_j}\left(e^{T_{fh}}\right)^{\omega_f}.$$

To simplify the model, we ignore the iceberg transportation cost of the FDI input because a model with the transportation cost also includes the distance in the cost function and thus is isomorphic to the current model.

Combined with domestic intermediate inputs, the price index of intermediate inputs from industry j is $P_{jh} = P_j\eta^{-\kappa_j}(G_{jh})^{\kappa_j}$. Aggregating all intermediate input prices from each upstream industry, the intermediate input price index for firm h is

$$P_h^x = \prod_j\left(P_j\right)^{\alpha_{ji}}\prod_j\left(\eta^{-\kappa_j}\right)^{\alpha_{ji}}\prod_j\left((G_{jh})^{\kappa_j}\right)^{\alpha_{ji}}.$$

Note that in the input price index for firm h, the first component $\prod_j\left(P_j\right)^{\alpha_{ji}}$ is the product of upstream industry price index and observable in data. The second and third components jointly represent the spillovers.

As the input expenditure of firm h equals the product of inputs and the input price index: $M_h = P_h^x \cdot X_h$, we solve the inputs of firm h as

$$X_h = M_h/P_h^x = M_h\prod_j\left(P_j\right)^{-\alpha_{ji}}\prod_j\left(\eta^{\kappa_j}\right)^{\alpha_{ji}}\prod_j\left((G_{jh})^{-\kappa_j}\right)^{\alpha_{ji}}. \tag{2}$$

Remark. All qualitative results of this model will not change if we alternatively assume that prices of domestic and FDI intermediate inputs in each upstream industry are different. Assuming the prices of domestic and FDI intermediate inputs are P_{1j} and P_{2j} respectively and $P_{1j}/P_{2j} = \xi$, the price of industry-j intermediate input is $P_{jh} = P_{1j}\eta^{-\kappa_j}\xi^{-\kappa_j}(G_{jh})^{\kappa_j}$. If we define $\tilde{\eta} \equiv \eta\xi$ as the price-adjusted productivity-enhancing parameter, all results hold.

2.2 *The benchmark estimation equation*

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

$$\begin{aligned} y_{ht} - \gamma_k k_{ht} - \gamma_l l_{ht} - \gamma_x \big(m_{ht} - \sum_j \alpha_{ji} p_{jt}\big) \\ = a_{ht} + \underbrace{\gamma_x ln(\eta) \sum_j \alpha_{ji}\kappa_{jt}}_{\text{General productivity-enhancing effect}} - \underbrace{\gamma_x \sum_j \alpha_{ji}\kappa_{jt} ln\big(G_{jht}\big)}_{\text{Proximity effect}}, \end{aligned} \tag{3}$$

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 first channel $\gamma_x ln(\eta) \sum_j \alpha_{ji}\kappa_{jt}$ represents the general productivity-enhancing effect of intermediate inputs from FDI firms. It describes how domestic firms benefit from the overall contribution of FDI in intermediate inputs. The second channel $\gamma_x \sum_j \alpha_{ji}\kappa_{jt} ln\big(G_{jht}\big)$ is the proximity effect, which 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 $ln\big(TFP^m_{ht}\big)$:

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

$m^r_{ht} \equiv m_{ht} - \sum_j \alpha_{ji} p_{jt}$ is the real intermediate input expenditure of firm h observed in data.

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 $ln\big(TFP_{ht}^m\big)$ in detail in the next section.

The general productivity-enhancing effect. When more FDI flows into China or existing FDI firms have higher domestic sales, domestic firms can get 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 the share of foreign ownership for firm f in period t; $(Y_{ft}-EX_{ft})$ 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, weighted by the input usage ratio α_{ji} from the input-output matrix.

The proximity effect. Intuitively, firm h has an easier access to FDI inputs if new upstream FDI firms start operation near its location, or if nearby existing FDI firms increase their market share. In contrast, the exit or the shrinking sales of existing FDI firms impede firm h from acquiring FDI inputs. We formalize the idea of the proximity effect by explicitly writing out a distance statistic between firm h and its upstream FDI firms. We define the market share of intermediate inputs from FDI firm f as

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

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 distance statistic can be written as

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

where $dist_{ht}$ is the double weighted average distance between firm h and its upstream FDI firms. It is weighted in two tiers: α_{ji}, the relative importance of 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 relative importance 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 distance statistic could provide a good approximation for the firm-level accessibility to FDI intermediate inputs.

The 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.

Our key estimation assumption is that the growth of overall upstream FDI inflow and upstream FDI firms' market behavior change, due to the relaxed FDI policy, are exogenous to firm h, and firm h is too small to reversely affect the aggregate FDI inflows in all upstream sectors. Therefore, the policy-induced changes in the upstream FDI inflows affect the productivity of firm h through two components—$forward_{it}$ and $dist_{ht}$. Specifically, FDI-encouraging policies can attract more FDI and increase κ_{jt}—the share of FDI inputs from industry j in $forward_{it}$. Upstream FDI firms' reaction upon this policy shock also alters G_{jht} and thus $dist_{ht}$ through adding or subtracting pairwise distances between firm h and its upstream FDI firms (entry and exit), or updating the input sales weight on the pairwise distances (market share change).

The coefficient β_1 represents how the general productivity-enhancing effect of FDI intermediate inputs varies with the relative contribution of upstream industry FDI in intermediate input supply to domestic firms. We predict $\beta_1 > 0$ because the prominence of FDI in upstream industries could strengthen the productivity of downstream domestic firms through their intermediate inputs. The coefficient for the term $dist_{ht}$, β_2, demonstrates how the geographical distance statistic between domestic firms and upstream FDI firms heterogeneously affects the productivity spillovers. 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 domestic firms' geographic proximity to upstream FDI firms plays an important role on the productivity spillovers through the availability of FDI intermediate inputs.

Remark. 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 distance statistic becomes a constant:

$$\sum_j \alpha_{ji}\kappa_{jt} ln(G_{jht}) = \sum_j \alpha_{ji}\kappa_{jt} \big(\sum_{f\in\Omega_{ft}} \omega_{ft} T \big) = T \sum_j \alpha_{ji}\kappa_{jt},$$

using $\sum_{j\in\Omega_{jt}} \omega_{ft} = 1$. Then the benchmark estimation equation (8) degenerates to

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

3 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 all manufacturing firms in China with sales revenue greater than 5 million Chinese yuan[5] between 2000 and 2007, approximately 122,000 firms on average in each year. This firm-level dataset is collected through Annual Surveys of Industrial Production by National 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.

Besides the 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 drop observations with missing or negative values of sales, employment, or firm age, reducing the sample to 928,387 firm-year observations (with 613,606 Chinese domestic firm-year observations) in 30 manufacturing industries. Even though 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 as multinational firms tend to be large in size (Helpman, Melitz, and Yeaple, 2004).

3.1 *FDI in China*

Since 1978, China has started the open trade policy and allowed inward FDI, though the volume and industries of FDI were strictly limited initially. In 1995, the Chinese central government published "Catalogue for the Guidance of Foreign Investment Industries" that provided guidelines for regulating FDI for the first time.

After China joined WTO in 2001, the Chinese central government has relaxed its inward FDI policies in a number of dimensions. The first dimension is industry. The Chinese central government updated "Catalogue for the Guidance of Foreign Investment Industries" twice and the updated versions became effective on April 2002 and January 2005 respectively. The revisions of industry guide allowed international investors to enter or increase their ownership in an extensive list of

[5] Approximately US $600,000 at the exchange rate in 2005.

industries that restricted or prohibited FDI before.[6] The second dimension is region. The Chinese central government updated "Catalogue of Priority Industries for Foreign Direct Investment in Middle and Western China" in 2004, which prompted FDI in more industries that were crucial to the development of the middle and western area. The third dimension is the type of investment. Besides the greenfield investment, the Chinese central government published interim provisions for foreign investors on restructuring state-owned enterprises and merging domestic enterprises in 2003, encouraging FDI through merger and acquisition.[7]

Consequently, FDI has grown explosively during the time span of our data. Moreover, the series of FDI supporting policies became effective quickly and broadly during a short period, and it was almost impossible for economic agents to predict the exact coverage and content of those policies and play the "market timing" game. Therefore, we can treat the escalating FDI inflow in our data as mainly induced by the plausibly exogenous policy shock.

In this paper, foreign subsidiaries are defined as firms with the share of subscribed capital from foreign countries, Hong Kong, Macau, and Taiwan of at least 10 percent, consistent with the literature. The number of FDI firms increases by 141% from 23,917 to 57,577 between 2000 and 2007. The average foreign capital share within a firm grows from 16.51% in 2000 to 29.95% in 2007. Among 30 manufacturing industries, communication equipment and computers, transportation equipment, and chemical products rank top three of FDI targeting industries and absorb 36.7% of total FDI in 2007. Culture, education and sport activity products, communication equipment and computers, and apparel are top three industries in terms of the average firm-level foreign capital share.[8]

For robustness, we also employ an alternative foreign capital share cutoff at 25 percent to define FDI firms, since the Chinese law entitles firms with more than 25% foreign capital share to preferential corporate tax rates offered for FDI firms.

[6] See Prasad and Wei (2007) and Lu, Tao, and Zhu (2017).

[7] See Wang and Wang (2015) for FDI through merger and acquisition in China between 2000 and 2007.

[8] These numbers are aggregated by the authors using the Chinese firm-level data.

3.2 *Constructing key variables*

To test the relationship between firm productivity and inputs from upstream FDI firms according to the benchmark regression Eq. (8), we need to construct measures for firm-level productivity, upstream FDI intermediate input share (for the general productivity-enhancing effect), and distance statistics (for the proximity effect).

Measured total factor productivity. We estimate firm-level productivity by employing the Ackerberg, Caves, and Frazer (2015) method that 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. More details are in Appendix A.

Upstream FDI intermediate input share. We use the weighted average upstream FDI intermediate input share defined in Eq. (5) as a measure for the portion of FDI inputs that a domestic firm purchases. We first calculate the foreign capital share for each individual firm. Then we generate the two-digit industry aggregate FDI domestic sales share using foreign capital shares as the weights. Lastly we employ the input-output matrix from *China Statistical Yearbook* to get the upstream FDI intermediate input share.

Firm-level accessibility to upstream FDI firms. In our regressions, we use the weighted average distance between a domestic firm and its FDI inputs suppliers defined in Eq. (7) to measure this domestic firm's accessibility to FDI intermediate inputs. Firm location is documented in our data, which enables us to calculate the distance between any two firms, and then the double weighted average distance between a domestic firm and its upstream FDI firms. Note that we need to calculate the distance statistic for each domestic firm, not for each region, and the large volume of calculation pays off to identify the heterogenous productivity spillovers at the firm level.

Administrative areas in China are divided into three tiers—provinces (also municipalities and autonomous regions), cities, and districts. A location is uniquely identified by a 6-digit district code that reflects all three tiers with the first two digits referring to the province, the middle two digits to the city, and the last two digits to the district.[9] The Annual Surveys of Industrial Production provides firm locations at the district level. 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.[10] Ideally, one may expect to measure the actual distance between any two districts through highways, country roads, or railroads. However, the development of transportation system in China has accelerated in the time span of the data; with no information on historical records of transportation networks, it is impossible to obtain the measure of actual transportation distances between two districts in past years. Therefore, the great circle distance is the best approximation we can achieve.

As shown in Figure 2, we first calculate distances (unit: km) between Chinese domestic firm h in industry i and FDI firms $f = 1, 2, 3, \cdots, n_j$ in upstream industry j. We denote these distances as d_{1h}, d_{2h}, d_{3h},$\cdots$, $d_{n_j h}$. Then we calculate the first-tier weighted average distance for this upstream industry j, where the first-tier weights are the domestic sales shares of FDI firm f, indicating the relative importance of firm f in serving inputs. We repeat this weighted average distance calculation for all upstream industries. Finally, we calculate the second-tier weighted average of these mean distances between firm h and FDI firms in each upstream industry, where the second-tier weights are from the input-output matrix of China.

After China's accession to WTO, the quick growth of FDI inflow stimulates more entry of FDI firms and a large increase in domestic sales of FDI incumbents. And therefore, this double weighted average distance for domestic firm h changes every year and the variation in the distance statistic enables us to identify the proximity effect.

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

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

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

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*

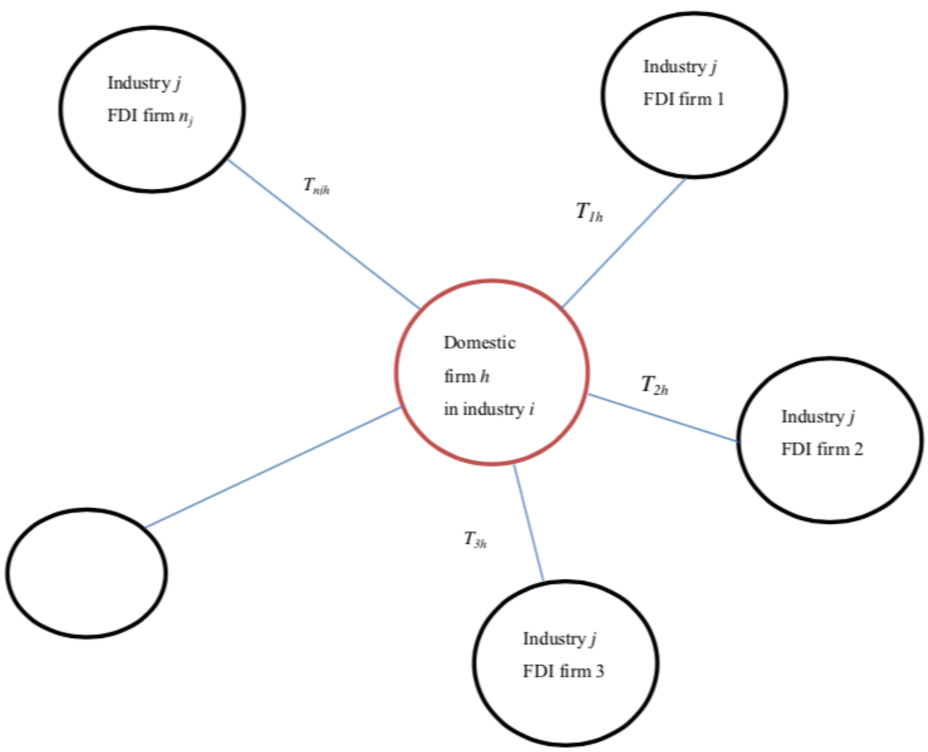

Fig. 2: A Firm's Distance Distribution

3.3 *Summary statistics*

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 3.319 with a standard deviation 1.407. We report upstream FDI intermediate input share *Forward* and a domestic firm's accessibility to FDI inputs *Forward distance* for two criteria of FDI firms—foreign capital share no less than 10% and 25%. There are more domestic firms observations if the definition of FDI firm is stricter (25% foreign capital share). The average upstream FDI input shares under two definitions of FDI firms are 15.26 percentage points and 14.86 percentage points respectively. 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—43.45 km and 42.22 km respectively under two different definitions of FDI firms.

Table 1: Summary Statistics

Panel A: Dependent and Key Independent Variables

Variables	No. of Obs.	Mean	Std. Dev.
ln(TFP)	613,606	3.319	1.407
Forward (%) – 10%	613,606	15.259	6.261
Forward distance (km) – 10%	613,606	43.448	24.637
Forward (%) – 25%	629,621	14.862	6.209
Forward distance (km) – 25%	629,621	42.217	24.093
Panel B: Industry and Province level Control Variables			
Variables	No. of Obs.	Mean	Std. Dev.
HHI	613,606	275.368	434.698
Real GDP (b. CNY)	613,606	892.282	647.890
Road per km^2 (km)	613,606	0.623	0.360
No. of R&D scientists per thousand persons	613,606	38.490	36.170
Real Imports (b. CNY)	613,606	310.680	456.484
Real Exports (b. CNY)	613,606	376.990	570.412
Panel C: Firm level Control Variables			
Variables	No. of Obs.	Mean	Std. Dev.
Firm age	613,606	13.264	13.961
State and Collective ownership	613,606	0.384	0.486
Mixed ownership	613,606	0.312	0.463

Note: ln(TFP) is firm-level measured productivity. Forward is the portion of domestic sales contributed by foreign capital in upstream industries. Forward distance refers to a local firm's weighted average distance to its upstream FDI firms. We measure two sets of Forward and Forward distance by using different definitions of FDI firms—10% foreign capital share as FDI firms and 25% foreign capital share as FDI firms. HHI is measured at 4-digit industry-time level. Real GDP, road per km^2, the number of R&D scientists per thousand persons, real imports and real exports are at the province-time level (with year 2000 as the base year). Firm age and firm ownership are measure at firm-time level. 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, the collective, the private, or other entities through the stockholding. Private ownership is used as the benchmark.

Panel B and Panel C report other major control variables under the 10% capital share FDI definition. The mean of HHI indicates that China on average has a relatively competitive domestic market; the comparison between real GDP, real imports, and real exports at the province level shows that China has been opening to trade between 2000 and 2007.[11] In our sample, we only focus

[11] Data resource: *China Statistical Yearbook*.

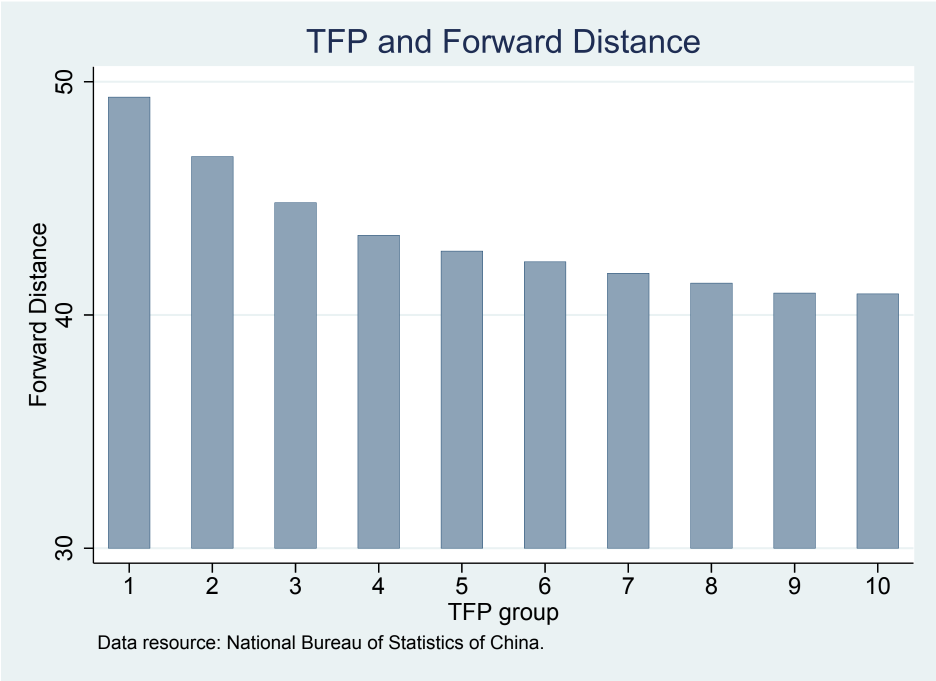

Fig. 3: Productivity and Distance Statistic

Note: TFP groups are the decile groups of Chinese domestic firm productivity between 2000 and 2007. Groups 1 to 10 include least to most productive domestic firms respectively. The distance statistic is the weighted mean distances between a domestic firm and its upstream FDI suppliers. FDI firms are defined as firms with foreign capital share no less than 10%.

on Chinese domestic firms. Among them, 38% are state owned or collectively owned enterprises, 31% firms have mixed ownership, and the rest 31% are private owned. In the empirical analysis, we use the firms with private ownership as the reference group. Besides, the average age of a domestic firm is a little above 13 years.

Figure 3 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 the distance statistic—*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—productivity spillovers from upstream FDI firms are mitigated if a domestic firm is geographically remoter to its FDI input suppliers.

4 Results

In this section, we first present the preliminary results using the Ordinary Least Square (OLS) regressions, then the benchmark results employing the fixed effects panel regressions. We further consider a variety of robustness checks that include other FDI spillover channels, labor and capital-good market externalities, upstream aggregate domestic productivity, imported inputs, and firms' endogenous location choice. 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 *Preliminary results*

We first estimate the benchmark model Eq. (8) with the pooled OLS regressions, in order to show that the core relationship between productivity spillovers and the distance statistic can pass the simple but powerful check without relying on complicated estimation technique. We report estimation results for both FDI firm definitions in Panel A (10% foreign capital share as FDI firms) and Panel B (25% foreign capital share as FDI firms) respectively of Table 2.

Besides the time fixed effects and 2-digit industry fixed effects, we also control for the time-varying 4-digit industry concentration ratio (Herfindahl-Hirschman Index), and some time-varying local factors that may influence the measured productivity of Chinese domestic firms. Following Sun, Tong, and Yu (2002) and Chen and Moore (2010), we add real GDP for market capacity, road per km^2 for infrastructure development, the number of scientists per thousand persons for research intensity, and real imports and real exports for openness at the province-time level. Firm-time level controls include firm age and firm ownership (state and collective ownership and mixed ownership, private ownership as the benchmark).

Table 2: Preliminary Results

Panel A: Pooled OLS estimation—10% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0084^{***}	0.0071^{*}	0.0193^{***}	0.0069
	(0.0027)	(0.0039)	(0.0050)	(0.0043)
ln(Forward distance)	-0.2175^{***}	-0.1538^{*}	-0.2176^{***}	0.0733
	(0.0506)	(0.0902)	(0.0629)	(0.0674)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs	613,606	395,348	144,190	74,068
R-squared	0.3660	0.3258	0.4146	0.4081

Panel B: Pooled OLS estimation—25% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0084^{***}	0.0072^{*}	0.0190^{***}	0.0071^{*}
	(0.0027)	(0.0039)	(0.0049)	(0.0042)
ln(Forward distance)	-0.2212^{***}	-0.1613^{*}	-0.2151^{***}	0.0707
	(0.0507)	(0.0901)	(0.0628)	(0.0668)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs	629,621	409,536	145,484	74,601
R-squared	0.3659	0.3260	0.4139	0.4078

Note: All variable definitions are in Table 1. Other control variables include HHI at the industry-time level, real GDP, road per km^2, the number of R&D scientists per thousand persons, real imports and real exports at the province-time level, and firm age and firm ownership (state/collective ownership and mixed ownership) at the firm-time level. 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; western China area includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Gansu, Shaanxi, Qinghai, Ningxia, and Xinjiang. Robust standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

The first specification in Table 2 presents the results including all domestic firms in China. 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.[12] The eastern region has embraced greater openness to the world and experienced faster growth; middle and western regions, due to their geographic disadvantages and historical conservativeness, have grown relatively slowly. Because of the differentiated developments across regions in China, domestic firms may have different capacities to absorb advanced technologies, and therefore knowledge transfers through intermediate inputs may also be different. Specifications (2) to (4) report the results from these three regional subsamples respectively.

The coefficients of *Forward* and *Forward distance* are consistent with our model predictions. An increase in the contribution of upstream FDI generates positive productivity spillovers to Chinese domestic firms (general productivity-enhancing effect), and the effect is weakened if a domestic firm is geographically remoter to its upstream FDI firms (proximity effect). From Column (1) of Panel A , if a Chinese domestic firm's upstream FDI intermediate input share is 1 percentage point larger, the productivity of this firm is 0.84% higher. If this firm is 10% geographically remoter to its upstream FDI firms, its productivity is on average 2.18% lower.

Except the western economic region, both eastern China and middle China show similar general productivity-enhancing effect and proximity effect from the existence of upstream FDI firms. In addition, the results are not sensitive to different FDI firm definitions (Panel A versus Panel B).

[12]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.

4.2 *Benchmark results*

Although Table 2 provides us a first check, the OLS estimation may be biased due to the unobserved firm-level heterogeneity. In order to deal with this potential bias by assuming that the unobserved firm-level heterogeneity is time-invariant, we estimate the benchmark model Eq. (8) by employing the fixed effects panel regressions. Alternatively, we apply the dynamic panel-data difference generalized method of moments (GMM) regressions to take the total factor productivity persistence into account. The results are robust. We discuss this estimation in details in Appendix B.

Similarly we report the results defining FDI firms with 10% foreign capital share and defining FDI firms with 25% foreign capital in Panel A and Panel B respectively, of Table 3. We control for the time and industry specific effects[13] and include all the industry-time, province-time and firm-time control variables used in the previous OLS estimations.

In Panel A (Table 3), Column 1 presents the results including all domestic firms in China. Again, the coefficients of *Forward* and *Forward distance* get aligned with our model predictions — a higher contribution of upstream FDI in intermediate inputs generates positive productivity spillovers to Chinese domestic firms (general productivity-enhancing effect), and the effect is mitigated if a domestic firm is farther away from its upstream FDI firms (proximity effect). Specifically, if a Chinese domestic firm's upstream FDI intermediate input share increases by 1 percentage point, the productivity of this firm will increase by 2.15%. In addition, if this firm is 10% geographically farther away its upstream FDI firms, its productivity is on average 1.42% lower than an otherwise identical firm.

Columns 2 to 4 in Panel A of Table 3 present the estimation results for the productivity spillovers for three economic regions respectively. The results for different regions are both qualitatively and quantitatively consistent with the benchmark full-sample results (Column 1).

[13]Some firms switch their primary industry across years. Therefore, we need to control for industry fixed effect besides firm fixed effect.

Table 3: Benchmark Results

Fixed effects panel regressions

Panel A: 10% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0215^{***}	0.0146^{***}	0.0162^{***}	0.0189^{***}
	(0.0014)	(0.0009)	(0.0019)	(0.0022)
ln(Forward distance)	-0.1417^{***}	-0.0250^{**}	-0.0704^{***}	-0.1419^{**}
	(0.0175)	(0.0127)	(0.0201)	(0.0707)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	613,606	395,348	144,190	74,068
No. of firms	239,855	157,905	56,425	25,530
R^2	0.3028	0.3204	0.3415	0.3029

Panel B: 25% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0216^{***}	0.0146^{***}	0.0164^{***}	0.0193^{***}
	(0.0011)	(0.0095)	(0.0025)	(0.0033)
ln(Forward distance)	-0.1440^{***}	-0.0369^{***}	-0.0671^{***}	-0.1420^{***}
	(0.0169)	(0.0070)	(0.0188)	(0.0271)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	629,621	409,536	145,484	74,601
No. of firms	245,291	162,812	56,805	25,679
R^2	0.3037	0.3208	0.3407	0.3034

Note: All variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

In Panel B of Table 3, we define FDI firms in a different way—firm with more than 25%

capital share as FDI firms, and therefore there are more firms being domestic firms. All results are consistent with the benchmark results—Chinese domestic firms can gain higher productivity through the channels of (i) larger upstream FDI share (general productivity-enhancing effect) and (ii) shorter distance to upstream FDI firms (proximity effect).

Since the regression results are not sensitive to the different definitions of FDI firms at all, we only report results using 10% capital share as FDI firms in our later robustness checks.

4.3 *Other FDI spillover channels*

Besides the forward productivity spillover effect, the literature on FDI spillovers also documents other FDI productivity spillover channels, namely the horizontal and the backward spillover effects.[14]

The FDI horizontal productivity spillover effect refers to the potential productivity spillovers from the existence of multinational subsidiaries in the same industry of any domestic firm. Multinational subsidiaries have a strong incentive to prevent information leakage to their host-country competitors in the same industry; and moreover, the competition pressure from the more productive multinational subsidiaries may depress less productive domestic firms, and some of them may exit the market. Therefore this spillover effect tends to be negative for many FDI host countries. We include the contribution of foreign capital in sales in each industry: $Horizontal_{it} = \frac{\sum_{f \in i} fshare_{ft} Y_{ft}}{\sum_{f \in i} Y_{ft}}$ to control for this productivity spillover channel.

The FDI backward spillover channel is believed through the contracts and transactions between downstream multinational subsidiaries and their upstream domestic suppliers. In this case, foreign subsidiaries are willing to provide some knowledge to their domestic intermediate inputs suppliers in order to guarantee the quality of their inputs. Consequently the backward spillover effect is typically positive. We use the weighted average foreign capital share from all downstream industries for any firm to control for the FDI backward productivity spillover effect: $Backward_{it} =$

[14] See Javorcik (2004) and Liu (2008).

$\sum_k \rho_{ik} \frac{\sum_{f \in k} fshare_{ft} Y_{ft}}{\sum_{f \in k} Y_{ft}}$, where ρ_{ik} is the portion of industry i output supplied to industry k.

Table 4: Other FDI Spillover Channels

Fixed effects panel regressions

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0171^{***}	0.0158^{***}	0.0142^{**}	0.0176^{**}
	(0.0014)	(0.0013)	(0.0064)	(0.0078)
ln(Forward distance)	-0.1330^{***}	-0.0212^{***}	-0.0560^{**}	-0.1559^{***}
	(0.0204)	(0.0059)	(0.0269)	(0.0391)
Horizontal	-0.0018^{***}	-0.0030^{**}	-0.0040	0.0043
	(0.0003)	(0.0013)	(0.0034)	(0.0029)
Backward	0.0060^{***}	0.0025^{**}	0.0067^{**}	-0.0360^{***}
	(0.0014)	(0.0010)	(0.0031)	(0.0037)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	613,606	395,348	144,190	74,068
No. of firms	239,855	157,905	56,425	25,530
R^2	0.3026	0.3205	0.3416	0.3032

Note: Horizontal measures the weighted average foreign capital contribution in sales in the firm's own industry, while Backward measures the extent of foreign capital contribution in sales from all downstream industries of the firm. All other variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

All regression specifications in Table 4 control for both FDI horizontal and backward spillover channels. Specification (1) includes all domestic firms in China, and (2) to (4) apply the same regression to eastern China, middle China and western China subsamples respectively. Consistent with the literature, the FDI horizontal spillover effects are mostly negative, while the backward spillover effects are generally positive. Moreover, there is no change in the statistical significance for the general productivity-enhancing effect or the proximity effect through FDI intermediate inputs; and there is very minor change in the economic significance for both effects. Domestic downstream firms do benefit from the existence of FDI intermediate inputs and this effect decays with the geographical distance.

4.4 *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, these firms are more likely to hire better trained and more skilled workers who have worked for foreign subsidiaries; as a result, these firms may receive more spillovers through workers' mobility (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 re-employed after quitting or losing their current jobs. Both mechanisms through the local labor market help to reduce the average production cost and improve firm-level productivity. In order to prove that the benchmark regression results are truly the results through FDI intermediate inputs, we need to control for the labor market externality.

Following Alfaro and Chen (2014), we calculate the likelihood that workers can find new jobs at the city level. We first use a 1% mini-census survey in 2005[15] that contains numbers of employees in detailed occupations for each industry. After transforming the employment counts of occupations to percentages, we write out the occupation percentage vector for every industry. Secondly, we find out the employment similarity for every industry pair by computing the correlation of the occupation vectors for these two industries. We then combine all the bilateral employment similarities into an employment similarity matrix. Thirdly, the likelihood of a worker being re-employed in a given city is determined by the employment similarity between his or her original and potential employers, and by the relative size of the original and new industries. Therefore, in a

[15] Data resource: National Bureau of Statistics.

given city, the probability for workers in an industry to be re-employed 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 a new job, the output share of each industry represents the likelihood that the worker will enter; the employment similarity between the original and new industries serves as a proxy for the probability that the worker is able to find a job. Summing up the probabilities for all industries in the city, we can measure the labor market externality at the city-time level. The measure of labor market externality is time-varying because the portions of industry outputs in a given city are changing over time, even though the employment similarities between industries are time-invariant.

Ellison et al. (2010) also documents that industries may agglomerate because of goods. Alfaro and Chen (2014) further points out that firms in different industries may be connected not only through intermediate inputs, but also through capital goods. Agglomerating firms can obtain better supports for their capital goods because of the scale economies, and reduce their risks in investment because of resale opportunities. If domestic firms agglomerate with upstream FDI firms and therefore are geographically closer to FDI firms, they may also benefit from capital-good market externality, because multinational firms are generally capital intensive. Then to waive the concern that the benchmark results are actually caused by the channel of capital-good market externality, we also need to control for the potential capital-good market externality.

Our challenge is to find a proxy for the likelihood that capital goods in one industry can be shared or re-sold to other industries in a given city. Ideally we should have detailed data on the use of a variety of capital goods at the industry level in China. However, National Bureau of Statistics of China does not provide such information. Assuming that usage of different types of capital goods is an intrinsic industry characteristic that is reserved across countries, we employ the US capital flow table.[16] We first calculate the capital-good usage vector for each industry according to the US capital flow table, where every element in the vector represents the percentage

[16]Data resource: US Bureau of Economic Analysis.

usage of a capital good in the industry. Second, the capital-good similarity for any industry pair is the correlation of capital-good usage vectors for those two industries. Third, in a given city, the probability for capital goods to be shared or resold locally is the weighted sum of capital-good similarities between the original industry and all other industries, where the weights are the output shares of each industry. Similar to the measure of labor market externality, the measure of capital-good externality is also time-varying because the output weights of industries in a given city change over time.

Table 5: Labor Market and Capital-good Market Externality

Fixed effects panel regressions

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0211^{***}	0.0138^{**}	0.0154^{***}	0.0177^{***}
	(0.0014)	(0.0008)	(0.0019)	(0.0022)
ln(Forward distance)	-0.1498^{***}	-0.0268^{*}	-0.0805^{**}	-0.1547^{***}
	(0.0187)	(0.0141)	(0.0319)	(0.0438)
Labor market externality	0.1713^{***}	0.1725^{***}	0.2112^{***}	0.2505^{***}
	(0.0309)	(0.0253)	(0.0449)	(0.0306)
Capital-good market externality	0.1274^{***}	0.1241^{***}	0.2711^{***}	0.2047^{*}
	(0.0363)	(0.0241)	(0.0701)	(0.1101)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	613,606	395,348	144,190	74,068
No. of firms	239,855	157,905	56,425	25,530
R^2	0.3041	0.3211	0.3437	0.3057

Note: 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 re-sold within a city. All other variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 5 presents the results after controlling for both labor market and capital-good market externalities, with Column 1 including all domestic firms in China and Column 2 to 4 reporting the results by regions. The coefficients of labor market externality and capital-good market externality are both positive and significant, indicating that Chinese domestic firms simultaneously benefit from these two markets. Besides these channels, the benchmark results are robust both qualitatively and quantitatively.

4.5 *Upstream aggregate domestic productivity*

We assume homogeneous domestic intermediate inputs in order to simplify our theoretical model and focus on the productivity spillover effects from upstream FDI firms. However, in reality, better upstream domestic firms are also likely to generate positive productivity spillover effects to downstream domestic firms. And hence, we calculate the upstream aggregate domestic productivity for each two-digit industry and add this variable to our benchmark regression to control for the potential spillover effect from upstream domestic firms. We first calculate the weighted average productivity of all domestic firms for each two-digit industry using firms' real total production as the weights.[17] Then we apply the input usage shares from China's input-output table to generate the upstream aggregate domestic productivity.

Table 6 reports the estimation results that include the upstream aggregate domestic productivity as an additional control variable. The first specification include all Chinese domestic firms, and the latter three employ regional subsamples. The coefficients of the upstream aggregate domestic productivity for all specifications are positive and significant with similar magnitudes, showing that more efficient domestic intermediate inputs suppliers also help to improve their corresponding downstream Chinese domestic firms' production efficiency. After controlling this domestic forward spillover effect, both the statistical and economic significances of the general productivity-

[17] We try using firms' real total sales as the weights as well, and different definitions of the upstream aggregate domestic productivity will not change our regression results.

enhancing effect and the proximity effect from FDI intermediate inputs do not change much.

Table 6: Upstream Aggregate Domestic Productivity

Fixed effects panel regressions

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0320^{***}	0.0193^{***}	0.0202^{***}	0.0195^{***}
	(0.0006)	(0.0008)	(0.0029)	(0.0030)
ln(Forward distance)	-0.0973^{***}	-0.0280^{***}	-0.0221	-0.1026^{***}
	(0.0127)	(0.0050)	(0.0363)	(0.0337)
Upstream Aggr. domestic productivity	0.6131^{***}	0.4032^{***}	0.4287^{***}	0.3001^{***}
	(0.0105)	(0.0071)	(0.0158)	(0.0375)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	613,606	395,348	144,190	74,068
No. of firms	239,855	157,905	56,425	25,530
R^2	0.3612	0.3223	0.3460	0.3067

Note: Upstream Aggr. (aggregate) domestic productivity is the weighted average productivity of all domestic firms from the upstream industries for the two-digit industry that the firm belongs to. All other variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

4.6 *Imported intermediate inputs*

Some of the domestic Chinese firms can get access to foreign varieties of intermediate inputs not only from FDI firms in China, but also from foreign exporters. In this case, these Chinese domestic firms are possible to gain additional technology spillovers from the imported intermediate inputs as Halpern et al. (2015) finds for Hungarian firms.

We would like to separate the effect of imported inputs from that of FDI inputs. We combine our data with the Chinese customs data, applying the method from Yu (2015). Chinese customs data contain highly disaggregated product-level information on both imports and exports, here we focus on the import information and add all the product-level import value together for each firm-year observation. Overall, 66% of foreign firms and 12.5% of domestic firms import inputs.

We divide the import value with the total production value for each firm to generate the imported input ratio, and control the imported input ratio for the potential spillovers from the imported intermediate inputs in the benchmark regressions.

Table 7: Imported Intermediate Inputs

Fixed effects panel regressions

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0215^{***}	0.0146^{***}	0.0161^{***}	0.0189^{***}
	(0.0015)	(0.0005)	(0.0032)	(0.0033)
ln(Forward distance)	-0.1418^{***}	-0.0243^{***}	-0.0706^{**}	-0.1418^{***}
	(0.0327)	(0.0083)	(0.0303)	(0.0380)
Imported Input Ratio	-0.8163^{***}	-0.7469^{***}	-1.1708^{*}	-0.5825
	(0.1315)	(0.1672)	(0.6160)	(1.0876)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
Industry controls	Yes	Yes	Yes	Yes
No. of obs.	613,606	395,348	144,190	74,068
No. of firms	239,855	157,905	56,425	25,530
R^2	0.3028	0.3205	0.3415	0.3030

Note: Imported input ratio is the total value of imported products over that of production. All other variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

The estimation results are shown in Table 7. Different from Halpern et al. (2015), imported intermediate inputs do not benefit Chinese firms in their productivity, and this 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 intermediate inputs are robust in both statistical significance and economic magnitude.

4.7 *The endogenous location choice by firms*

If the proximity effect does hold, it is possible that productive Chinese domestic firms self-select their locations to be closer to their upstream FDI suppliers. And thus, our proximity effect in the benchmark estimation may be biased. Because foreign direct investment started blowing into China after it joined WTO in 2001, we focus on a subsample of Chinese domestic firms which established before 2000 to mitigate this potential endogenous location choice. When these older Chinese domestic firms chose their locations to set up plants, they were not affected by a large portion of upstream FDI firms that entered China later than 2001.

In addition, multinational firms may also choose the optimal locations to establish their foreign affiliates. We have employed the exogenous FDI policy shock after China's accession to WTO in the benchmark result, capturing the policy-induced FDI allocation to the middle and western regions and industries that were restricted before. In this subsection, we consider other determinants for FDI firms' location choice. Foreign affiliates may cluster in some locations, and therefore the distance statistics from upstream FDI firms are smaller for the Chinese firms in these locations. The determinants of location choice can facilitate domestic firms improving their productivity. Specifically, a larger market size may cause tougher competition and thus firms need to employ better technology; good infrastructures may ease the learning process of technology. Consequently, the general productivity-enhancing effect and proximity effect estimations may be biased as a reflection of FDI location determinants.

We conduct a two-step estimation to correct the potential endogeneity problem that is raised by FDI location choice. We first estimate how likely multinational firms are to build up their affiliates for each location. Then, we add the estimated likelihood of FDI location choice as an additional control variable into the benchmark regressions.

In the first stage of the likelihood estimation, the dependent variable P_{rt} is a dummy variable that equals 1 if there is at least one FDI firm in that location (at the 6-digit district code level) and 0 otherwise. According to Cheng and Kwan (2000) and Amiti and Javorcik (2008), FDI-favoring policies affect multinational firms' location choice. The corporate income tax rate for firms registered in the economic zones ranges from 15% to 24%, while that for firms outside the economic zones is 30%.[18] Therefore, we use dummies of different types of economic zones at the district level X_{rt} as the proxies for the preferential policies. Following Chen and Moore (2010), we have two additional variables in our first stage estimation: the market potential and the unit labor cost at the provincial level. The market potential for province p in year t is defined as $MP_{pt} = \sum_q \frac{RGDP_{qt}}{d_{pq}}$, where d_{pq} measures the distance between the capital cities of provinces p and q, $RGDP_{qt}$ is the real GDP of province q in year t. This market potential variable captures the market sizes of all provinces for province p. The unit labor cost is calculated as the labor-quality-adjusted average annual real wage of workers at the provincial level.[19]

The FDI location choice in a district may be correlated across years. Therefore, we estimate the likelihood of FDI location choice by the random effects probit model to control for the serial correlation, instead of the pooled probit model.[20] The random effects probit model is

$$Pr(P_{rt} = 1) = \Phi(c + B_1 X_{pt} + B_2 X_{rt} + \epsilon_{rt}), \tag{9}$$

where Φ is the cumulative normal distribution, c is the constant, X_{pt} includes the market potential MP_{pt} and the log of the unit labor cost, and ϵ_{rt} is the residual.

[18] Data resource for the economic zones and their preferential policies in favor of FDI: *Investment in China* (www.fdi.gov.cn) and *China Economic Zones* (www.cadz.org.cn).

[19] Real wage is adjusted by the GDP deflator. We use the number of scientists per thousand people to represent the labor quality at the provincial level. Data source: *China Statistical Yearbook*.

[20] We also check other specifications such as the fixed-effects logit model. We do not use the fixed-effects panel probit model because it suffers from the incidental parameters problem, which results in the inconsistent estimation of coefficients, according to Wooldridge (2007).

Table 8: The Endogenous Location Choice of Domestic and FDI Firms

1st stage: Probit estimation (marginal effects)		2nd stage: Fixed effects panel regressions				
Dependent variable: FDI locating probability		Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
ln(Market potential)	4.183***	Forward	0.0183***	0.0171***	0.0481***	0.0519***
	(0.154)		(0.0020)	(0.0009)	(0.0014)	(0.0022)
ln(Labor cost)	−0.362**	ln(Forward distance)	−0.0904***	−0.1029***	−0.2106***	−0.3340***
	(0.168)		(0.0207)	(0.0389)	(0.0162)	(0.0563)
Economic and tech development zone	4.956***					
	(0.869)					
		Fitted FDI locating probability	Yes	Yes	Yes	Yes
		Other control v.	Yes	Yes	Yes	Yes
		Time controls	Yes	Yes	Yes	Yes
		Industry controls	Yes	Yes	Yes	Yes
No. of districts	3,209	No. of firms	150,057	93,375	35,343	17,342
No. of obs	21,447	No. of obs	425,799	272,645	98,529	54,625
Psudo R^2	0.068	R^2	0.2890	0.2620	0.3216	0.2539

Note: The first stage employs the Probit model and estimates the probability of whether FDI firms are located in a district. FDI locating probability for a district is defined as 1 if there is at least one FDI firm, 0 otherwise. Market potential at the province level is a weighted sum of real GDP, where the weights are the reciprocal of distances between the capital city for the province the district belongs to and other capital cities. Labor cost at the province level is the labor-quality-adjusted annual real wage for that province, where the labor quality is measured as the R&D investment (number of scientists per thousand). The dummy of economic and technological development zone is at the district level. The marginal effects are reported for the first stage. In the second stage, we only include domestic firms that were established earlier than 2000. We also control the fitted value of FDI locating probability. The control variables include firm age and ownership at the firm level, and road per km^2 at the province level. All other variables are defined in Tables 1 and 2. Bootstrapped standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Following the method to deal with unobserved variables in Chen and Moore (2010), we then add the predicted likelihood of FDI location choice $\hat{P}_{rt}$ into the fixed effects panel reressions by matching each firm's location with the 6-digit district r. Note that we also control firm age and ownership at the firm level, and road per km^2 at the province level. The real GDP, the number of scientists per thousand persons, and real imports and exports at the province level are not included because they are strongly correlated with the market potential, quality-adjusted labor cost, and economic zone dummies, and thus the fitted probability of FDI location choice.

Table 8 displays the estimation results after controlling for the FDI firms' location choice based on a subsample including only Chinese domestic firms established before 2000. In the first stage regression, the probability of whether FDI firms are located at a specific district is positively correlated with the market potential and the preferential policies from economic and technology development zone,[21] and negatively correlated with the unit labor costs. In the second stage, we add the predicted values of FDI location probability from the first stage for all regression specifications. The general productivity-enhancing effect and the proximity effect in all four specifications are qualitatively and quantitatively unchanged from our benchmark results after we control for the potential endogenous location choice by both FDI firms and domestic firms.

5 Conclusion

This paper quantifies the heterogeneous FDI forward productivity spillovers at the firm level. Focusing on the channel of FDI intermediate inputs, we model and empirically confirm the gravity effect in productivity spillovers—not only the relative contribution of FDI in upstream industries, but also the heterogenous distance statistics between domestic firms and upstream FDI firms affect the productivity spillovers.

[21]Economic and technology development zone is the most important type of economic zone in China. We only show the result for it in our first stage regression due to limited space. The coefficients of other economic zone dummy variables are also positive.

These findings further suggest that if policymakers want domestic firms to absorb productivity spillovers from FDI firms more efficiently, they need to design more precise stimulating policies according to domestic firms' differentiated access to FDI intermediate 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 achieve balanced regional economic growth.

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Appendix A

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

$$y_{hit}^{va} = \gamma_k k_{hit} + \gamma_l l_{hit} + a_{hit} + \epsilon_{hit}, \tag{A1}$$

where y, k and l stand for the logarithm of value-added real output[22], capital stock and total employment respectively, a denotes the technology parameter, ϵ is the residual, subscripts h, i and t stand for firm, industry and time, and γ_k and γ_l, the coefficients to be estimated, are capital's and labor's shares of output in industry i. 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 $t-1$; ξ_{hit} is the innovation of productivity at t and is 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 capital's and labor's share of output; the second step separates a_{hit} from ϵ_{hit}; the third step estimates γ_k and γ_l.

The first step does not need more explanation. In the second step, assume the firm chooses k_{hit} and l_{hit} in period $t-1$, and the real intermediate input m_{hit}^r in period t. We write the choice of the

[22]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 $Y_{hit}^{va} = (1-\hat{\gamma}_x)Y_{hit}$.

intermediate input as

$$m_{hit}^r = f_t(k_{hit}, l_{hit}, a_{hit}). \tag{A2}$$

Substituting (A2) to (A1) yields

$$y_{hit}^{va} = \gamma_k k_{hit} + \gamma_l l_{hit} + f_t^{-1}(k_{hit}, l_{hit}, m_{hit}^r) + \epsilon_{hit}. \tag{A3}$$

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

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

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

In the third step, we find two independent moment conditions in order 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

$$E[\xi_{hit} \begin{pmatrix} k_{hit} \\ l_{hit} \end{pmatrix}] = 0. \tag{A4}$$

We then estimate γ_k and γ_l by employing these two moment conditions in (A4). 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 (A4):

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

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

Appendix B

We re-estimate the benchmark model Eq. (8) by employing the dynamic panel-data two-step difference GMM estimations.[23] The dynamic panel-data difference GMM has two advantages. It first controls the persistence of firm-level productivity, as the current productivity level may depend on its past realizations (Bilir and Morales, 2016). In comparison with Javorcik (2004) that estimates the effect of productivity spillovers in differences, the dynamic panel-data difference GMM allows a more flexible form of persistence in firm-level productivity by estimating the persistence parameter directly. The difference GMM also eliminates the unobserved firm heterogeneity and generates efficient estimates. Specifically,

$$\Delta ln\big(TFP^m_{ht}\big) = \beta_0 + \beta_{tfp}\Delta ln\big(TFP^m_{ht-1}\big) + \beta_1\Delta forward_{it} + \beta_2\Delta dist_{ht} + \Delta\mathbf{x}_{ht} + \Delta\nu_{ht},$$

where β_{tfp} gauges the persistence of firm productivity, $\epsilon_{ht} = \mu_h + \nu_{ht}$, μ_h represents the unobserved time-invariant heterogeneity, ν_{ht} is the i.i.d. shock, and $E(\mu_h\nu_{ht}) = 0$.

[23]Please refer to Roodman (2009) for the proper use of the difference GMM estimators, which was developed by Holtz-Eakin, Newey, and Rosen (1988), Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998).

Table B1: Benchmark Results—Dynamic panel difference GMM

Dynamic panel-data estimation, two-step difference GMM

Panel A: 10% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0452^{***}	0.0337^{***}	0.0568^{***}	0.0487^{***}
	(0.0095)	(0.0107)	(0.0169)	(0.0167)
ln(Forward distance)	-0.5616^{***}	-0.4383^{***}	-0.5645^{**}	-0.4666^{*}
	(0.1398)	(0.1621)	(0.2508)	(0.2555)
Lagged ln(TFP)	0.1772^{***}	0.1782^{***}	0.1933^{***}	0.1435^{***}
	(0.0144)	(0.0195)	(0.0183)	(0.0321)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
No. of obs	199,397	126,179	45,332	27,886
No. of firms	83,338	52,401	20,114	10,823
Hansen test-p	0.000	0.075	0.140	0.119

Panel B: 25% foreign capital share as FDI firm

Dependent variable: ln(TFP)	All Regions (1)	Eastern China (2)	Middle China (3)	Western China (4)
Forward	0.0349^{***}	0.0236^{**}	0.0540^{***}	0.0448^{***}
	(0.0094)	(0.0107)	(0.0164)	(0.0173)
ln(Forward distance)	-0.4502^{***}	-0.3171^{**}	-0.5902^{**}	-0.4102^{*}
	(0.1284)	(0.1499)	(0.2441)	(0.2415)
Lagged ln(TFP)	0.1768^{***}	0.1828^{***}	0.1987^{***}	0.1396^{***}
	(0.0143)	(0.0193)	(0.0190)	(0.0317)
Other control v.	Yes	Yes	Yes	Yes
Time controls	Yes	Yes	Yes	Yes
No. of obs	205,765	131,806	45,840	28,119
No. of firms	85,932	54,732	20,296	10,904
Hansen test-p	0.000	0.077	0.174	0.226

Note: All variables are defined in Tables 1 and 2. “Hansen test-p" denotes the test of over-identifying restrictions. Robust standard errors are clustered at the city level and presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Similar to Table 3, Table B1 lists the results defining FDI firms with 10% foreign capital share and defining FDI firms with 25% foreign capital in Panel A and B respectively. We take care of the dynamic feature of firm-level total factor productivity by including the lagged term of TFP. Besides, we treat both upstream FDI intermediate input share *Forward* and firm-level accessibility to upstream FDI firms *Forward distance* as pre-determined variables[24].

In both panels (Table B1), Column 1 presents the results including all domestic firms in China. Columns 2-4 present the estimation results for the productivity spillovers for three economic regions respectively. The coefficients of *Forward* and *Forward distance* are consistent with our benchmark results. Specifically, for Column 1 in Panel A, the general productivity-enhancing effect is 4.52%, and the proximity effect is about -0.56%.

[24]Both *Forward* and *Forward distance* variables may be correlated with their past-period error terms.