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

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June 25, 2017

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Abstract

We develop a model to illustrate that upstream foreign direct investment (FDI) generates heterogeneous productivity spillovers toward downstream domestic firms through the gravity of intermediate inputs—a domestic firm enjoys a higher productivity if it gets access to more inputs sold by FDI firms (general productivity-enhancing effect) and it is geographically closer to upstream FDI firms (proximity effect). We employ Chinese firm-level data and empirically identity that (i) if a domestic firm's FDI input share increases by 1 percentage point, its productivity increases by 2.8%, and (ii) if this firm is 1% geographically remoter than an otherwise identical firm to upstream FDI firms (on average 3 kilometers), its productivity is 0.06% lower.

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

Keywords: FDI, productivity spillover, gravity effect, spatial diffusion, China

1 Introduction

Foreign direct investment (FDI) has been surging into developing countries and emerging markets since the 1990s. The net inflows of FDI to low- and middle-income countries in 2015 are 22.20 times more than the net FDI inflows to these countries in 1991.[1] Take China as an example, where foreign capital in manufacturing firms has more than tripled between 2000 and 2007, as shown in figure 1. The rapid growth of FDI is closely associated with the FDI stimulating policies such as tax reductions and entry subsidies, because policymakers in developing countries usually believe that FDI infuses advanced technology and generates positive externality to domestic firms.

Different from the conventional wisdom and policymakers' belief, extensive literature presents mixed evidence on the productivity spillovers of FDI toward domestic firms through a variety of channels.[2] Moreover, due to data availability, previous empirical papers in this trend of literature focus on the average impact of FDI productivity spillovers on domestic firms. For example, firms within one industry are affected uniformly by the existence of upstream or downstream FDI firms in Javorcik (2004). However, because of firm-level heterogeneity, domestic firms are affected by FDI differently in reality. Therefore, policymakers need to design targeted policies that align domestic firms with more precise incentives in order to help them absorb productivity spillovers better. The mixed evidence on FDI productivity spillovers and the limited understanding on spillover heterogeneity necessitate further investigations.

Our paper aims to explore one of the productivity spillover channels—the forward channel from upstream FDI firms, and the heterogeneous impacts of spillovers on domestic firms. We find the gravity effect of intermediate inputs in productivity spillovers—not only the portion of inputs from upstream FDI firms, but also the geographical distance distribution between domestic and upstream

[1] Data resource: World Bank Economic Development Indicators. Series Code: BX.KLT.DINV.CD.WD.

[2] See Aitken and Harrison (1999) and Harrison et al. (2004) on the channel of financing; Fosfuri et al. (2001) and Glass and Saggi (2002) on the channel of workers' mobility; 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 et al. (2013), and Gorodnichenko et al. (2014) find mixed evidence of positive productivity spillovers from FDI firms.

FDI firms—affects productivity spillovers. Specifically, in a production model, domestic firms minimize their production costs and face a tradeoff when exploiting intermediate inputs produced by upstream FDI firms—FDI inputs enhance firms' productivity but involve procurement costs associated with the geographic distance to upstream FDI firms. Incorporating the tradeoff on FDI inputs into the production function, we are able to decompose measured total factor productivity into a firm-level technology parameter, a homogeneous productivity-enhancing effect from FDI inputs, and a heterogeneous proximity effect that depends on the distance distribution between domestic and upstream FDI firms. The latter two effects indicate the channels through which domestic firms can absorb productivity spillovers from upstream FDI firms.

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. As intermediate inputs produced by multinational firms embody advanced technology (Keller and Yeaple, 2013), the cost-efficient FDI inputs and the associated technical supports could generate positive externality to domestic firms. If the contribution of FDI in upstream industries increases, either due to a larger amount of foreign direct investment, or due to more domestic sales by FDI firms, the general productivity-enhancing effect will be fortified. We use Chinese firm-level data between 2000 and 2007 to test this effect. With China's accession to the World Trade Organization (WTO), FDI firms' contribution toward input use in any downstream industry has grown quickly. We show that if a Chinese domestic firm's FDI input share increases by 1 percentage point, the productivity of this firm will increase by 2.8%.

The proximity effect indicates that domestic firms may be heterogeneously affected by FDI firms in the upstream industries based on their distance to these upstream FDI firms. We use the weighted sum of average distances between the domestic firm and FDI firms in each upstream industry—where weights are the input-output matrix parameters—as the distance statistics for each domestic firm. After China joined WTO, policymakers provided preferential policies to encourage FDI to flow into industries and regions that had been restricted. The entry and exit of upstream FDI firms change the distance distribution to a given domestic firm and therefore alter the productivity spillovers through the proximity effect. We find that if a Chinese domestic firm is 1% geographically remoter to its upstream FDI firms than an otherwise identical firm (on average 3 kilometers in our data set), its productivity is 0.06% lower.

Our empirical results are robust to (i) two measures of distance statistics—nationwide and within the province, and (ii) subsamples of east, central, and west regions. Moreover, after we control for the potential local labor and capital-good market externalities, upstream domestic firms' spillovers, FDI productivity spillovers from the same and downstream industries, imported intermediate inputs, and the endogenous firm location choice, benchmark results are still qualitatively and quantitatively unchanged.

This paper first contributes to the literature by creating a novel firm-level statistic of distance distribution between FDI and domestic firms and identifying how distance may obstruct productivity spillovers. Previous literature has discussed how the geographical remoteness impedes technology diffusion at the country level (Keller, 2002; Comin et al., 2012). This paper models and estimates the impact of distance distribution on FDI spillovers at the firm level by decomposing productivity spillovers into the gravity of intermediate inputs—the general productivity-enhancing effect and the proximity effect. These two effects jointly provide the supporting evidence on the existence of FDI productivity spillovers and help to measure the heterogeneity in productivity spillovers at the firm level. The impact of distance distribution further suggests that policymakers need to be aware of the geographical remoteness between domestic firms and their upstream FDI firms to help domestic firms absorb productivity spillovers; targeting domestic firms that are geographically remote to upstream FDI ultimately helps to achieve balanced regional economic development. Secondly, complementing the literature on the role of imported inputs in enhancing firm productivity in developing countries (Goldberg et al., 2010, Amiti, et al., 2014, and Halpern et al., 2015), this paper shows that policymakers can improve aggregate productivity by encouraging domestic firms to employ FDI inputs, especially in developing countries that have already attracted

FDI in upstream industries, paralleling tariff concession on imported intermediate inputs.

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 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 measured total factor productivity of domestic firms into three components: a firm-level technology parameter, the general productivity-enhancing effect through the inputs produced by upstream FDI firms, and the proximity effect that varies with domestic firms' geographical accessibility to upstream FDI firms. The latter two effects jointly reveal the gravity of intermediate inputs in productivity spillovers from upstream FDI firms. We then propose the benchmark estimation equation that identifies these two effects.

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. The intermediate input of firm h, X_h, is a composite of intermediate inputs

X_{ji} from upstream industries indexed by j:

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

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 input X_{ji} can be further decomposed to two varieties produced by domestic and FDI firms: X_{Dj} and X_{Fj}, which are imperfect substitutes in a Cobb-Douglas function:

$$X_{ji} = C_{i2}\left(X_{Dj}\right)^{1-\kappa_i}\left(\eta X_{Fj}\right)^{\kappa_i},$$

where $\kappa_i \in (0,1)$ is identical for all firms in industry i; $C_{i2} = (1-\kappa_i)^{1-\kappa_i}\kappa_i^{\kappa_i}$; η measures the productivity-enhancing effect of FDI intermediate inputs, and $\eta > 1$.[3] Amiti, et al. (2014), and Halpern, et al. (2015) document and model that imported inputs can enhance the productivity of domestic firms because these are more effective inputs for any downstream firm. Similarly, we assume that FDI intermediate inputs can also improve the productivity of downstream domestic firms.

In order to focus on the impacts of FDI intermediate inputs, we assume that inputs from domestic firms are perfect substitutes and then firm h only purchases from the closest domestic firm. The FDI inputs X_{Fj} consists of intermediate inputs from upstream FDI firms indexed by f:

$$X_{Fj} = C_{Fj} \prod_{f\in\Omega_j} \left(X_{fh}\right)^{\omega_j},$$

where Ω_j is the set of FDI firms in industry j, ω_j is the share of intermediate inputs sold by FDI firm f, $\sum \omega_j = 1$, and $C_{Fj} = \prod \omega_j^{\omega_j}$ is a constant. Note that we need to assume firm h purchases intermediate inputs from all upstream FDI firms since no firm-level input-output matrix is available

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

in our data.[4]

The intermediate input expenditure and production. Firm h minimizes its expenditure M_h on intermediate inputs X_h. There is an iceberg cost if firm h purchases intermediate inputs from FDI firm f located in a separate place; we use the distance between two firms T_{fh} to measure this iceberg cost. 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

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

where G_{jh} represents the aggregate iceberg cost. Similar to Keller (2002) and Ellison et al. (2010), distance T_{fh} is not only a proxy of transportation costs but also reflects technology diffusion costs that surge with distance, for example, the costs of communication and technology support associated with input purchase.

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

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

where the first term $\prod_j \left(P_j\right)^{\alpha_{ji}}$ reflects the overall role of upstream industry price indices, the second term $\prod_j \left(\eta^{-\kappa_i}\right)^{\alpha_{ji}}$ and the third term $\prod_j \left((G_{jh})^{\kappa_i}\right)^{\alpha_{ji}}$ jointly represent how the use of FDI inputs reduces domestic firm h's total expenditure on intermediate inputs. The second term illustrates cost-saving effect homogeneous to all domestic firms in industry i; the third term focuses on how the cost-saving effect may be weakened due to the firm-level heterogenous geographic remoteness to upstream FDI firms.

[4]Alternatively, we can assume that there is no fixed cost to purchase FDI intermediate inputs; then a firm can purchase intermediate inputs from all upstream FDI firms.

Finally, we can rewrite the production function (1) as:

$$Y_h = A_h\big(K_h\big)^{\gamma_k}\big(L_h\big)^{\gamma_l}\big(M_h\big)^{\gamma_x}\Big[\prod_j \big(P_j\big)^{\alpha_{ji}}\Big]^{-\gamma_x}\Big[\prod_j \big(\eta^{-\kappa_i}\big)^{\alpha_{ji}}\Big]^{-\gamma_x}\Big[\prod_j \big((G_{jh})^{\kappa_i}\big)^{\alpha_{ji}}\Big]^{-\gamma_x}. \tag{2}$$

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 $P^x_{ji} = P_{1j}\eta^{-\kappa_i}\xi^{-\kappa_i}(G_{jh})^{\kappa_i}$. 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 take the log of the production function (2) to generate an empirically testable estimation equation, adding time subscript t to each time-varying variable and applying $\sum_j \alpha_{ji} = 1$:

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

where the lower case letters indicate the logged variables. Below we describe how we define and measure each variable in Eq. (3).

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

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

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

Like Gopinath and Neiman (2014) and Halpern et al. (2015), we can only observe the industry-level price index of intermediate inputs p_{jt}, not the input price index for individual firms.

The right hand side of Eq. (3) is the total factor productivity of firm h, as in Halpern et al. (2015). The total factor productivity can be decomposed into a firm-level technology a_{ht} and two transmission channels of productivity spillovers. The technology parameter a_{ht}, unobservable in data, consists of a time-constant component $\bar{a}_h$, and a time-varying component ζ_{ht} that includes "the managerial ability of a firm, expected down-time due to machine breakdown, or expected defect rates in a manufacturing process" (Ackerberg, et al. 2015). The first channel $\gamma_x ln(\eta)\kappa_{it}$ 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.[5] The second channel $\gamma_x \kappa_{it} \sum_j \alpha_{ji} ln\left(G_{jht}\right)$ is the proximity effect, which depicts how domestic firms that are geographically remoter to upstream FDI firms benefit less from the forward productivity spillover.

Given that η and γ_x are constant, the general productivity-enhancing effect varies with κ_{it}, which is measured as the share of FDI intermediate inputs and fluctuates at the industry-time level. This effect is homogeneous for all domestic firms in an industry. As to the proximity effect, entry and exit of upstream FDI firms alter firm h's distance distribution to upstream FDI firms and these changes are exogenous to firm h. Changes in the distance distribution for firm h further affect productivity spillovers toward it.[6] We describe in detail how to construct κ_{it} and how to measure the distance distribution of firm h below.

Upstream FDI intermediate input share. 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 $forward_{it}$ in Javorcik (2004), we measure κ_{it} as the weighted average portion of FDI firms' outputs that sell in the

[5] This effect is also consistent with the forward effect in Javorcik (2004).

[6] We assume that firm h cannot relocate after it starts production.

domestic market:

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

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.[7]

Firm-level accessibility to upstream FDI firms. If the share of intermediate inputs from FDI firms in industry j is $\omega_{jt} = 1/n_{jt}$, where n_{jt} stands for the number of FDI firms of industry j in year t, then firm h's distance statistics in Eq. (3) can be written as

$$dist_{ht} \equiv \sum_{j} \alpha_{ji} ln\big(G_{jht}\big) = \sum_{j} \alpha_{ji} \omega_{jt} \sum_{f \in \Omega_{jt}} T_{fh} = \sum_{j} \alpha_{ji} \big(\sum_{f \in \Omega_{jt}} T_{fh}/n_{jt} \big), \tag{6}$$

where $dist_{ht}$ is the weighted mean for the distance distribution between firm h and upstream FDI firms. It is weighted in two tiers: the equal weight of all upstream firms in industry j ($\omega_{jt} = 1/n_{jt}$) and the relative importance of industry j in providing intermediate inputs to industry i (α_{ji}). Since firms in most data do not provide detailed information on intermediate input suppliers and therefore a firm-level input-output matrix is very rare, we believe these two-tier weights could provide a good approximation for the firm-level accessibility to FDI intermediate inputs.

The benchmark estimation. Substituting Eq. (4), (5) and (6) into Eq. (3) and adding the control

[7] Note that we adopt the measure of FDI contribution in inputs from Jacorcik (2004) to make our results comparable with previous literature. Given that it is exogenous to individual firms, κ_{it} is not derived from the input cost minimization problem.

variables and the firm-level error term, we obtain the benchmark estimation equation:

$$ln\big(TFP^m_{ht}\big) = \beta_0 + \underbrace{\beta_1 forward_{it}}_{\text{General productivity-enhancing effect}} + \underbrace{\beta_2 forward_{it} \cdot dist_{ht}}_{\text{Proximity effect}} + \mathbf{x}_{ht} + \delta_t + \delta_h + \epsilon_{ht}, \quad (7)$$

where $\mathbf{x}_{ht}$ is the vector of control variables, δ_t and δ_h are time and firm fixed effects respectively, and ϵ_{ht} is the error term that includes identically and independently distributed (i.i.d.) shocks and time-varying firm heterogeneity. Note that the time-constant component of technology $\bar{a}_h$ is absorbed by firm fixed effect δ_h, and the time-varying component of technology ζ_{ht} is covered by the error term ϵ_{ht}. We will discuss how to control for the potential effect from ζ_{ht} toward the measured total factor productivity in the next section.

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 interaction term $forward_{it} \cdot dist_{ht}$, β_2, demonstrates how the geographical distance distribution between domestic and upstream FDI firms heterogeneously affect the productivity spillovers. We predict $\beta_2 < 0$ because given $forward_{it}$, 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, but also domestic firms' geographic proximity to upstream FDI firms affect the productivity spillovers through the channel of intermediate inputs.

Remark. Eq. (7) is consistent with the estimation equation in Javorcik (2004) if all distances between domestic and upstream FDI firms are identical: $T_{fh} = T$. Specifically, if the firm-specific effect of distance distribution becomes a constant:

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

then the benchmark estimation equation (7) degenerates to

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

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 greater than 5 million Chinese yuan[8] 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 data also contain information on location, ownership, and employment. We drop observations with missing or negative values of sales or employment, reducing the sample to 929,365 firm-year observations (with 614,564 Chinese domestic firm-year observations) in 30 manufacturing industries. Even though it does not cover firms with sales 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.

Since 1978, China has started the open trade policy and allowed inward FDI, though the volume and industries of FDI were strictly limited innitially. In 1995, the Chinese central government

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

published "Catalogue for the Guidance of Foreign Investment Industries" that provided guidelines for regulating FDI. After China joined WTO in 2001, the Chinese central government modified the catalogue several times and started to encouraged FDI to enter industries that were previously restricted or prohibited. Consequently, FDI has grown explosively afterward. Our data cover the time period with the burst of inward FDI.

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. Foreign investment has been growing fast during the time span in the dataset. The number of FDI firms increases by 147% from 22,780 to 56,172 between 2000 and 2007. The average foreign capital share within a firm grows from 24.9% in 2000 to 37.5% in 2007. Among 30 manufacturing industries, communication equipment and computers, transport equipment, and chemical products rank top three of FDI targeting industries and absorb 36.6% 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.

3.1 *Constructing key variables*

To test the relationship between firm productivity and inputs from upstream FDI firms according to the benchmark regression Eq. (7), we need to construct measures for firm-level productivity, upstream FDI intermediate input share, and distance statistics.

Measured total factor productivity. Traditional productivity measures such as Solow residuals assume a firm's technology parameter is exogenous to its input factor choice. However, a firm may make decisions on labor and capital based on the expected machine breakdown time or other time-varying unobservable heterogeneity. Ignoring the endogenous factor choice may ultimately contaminate estimates of the spillover effects. Therefore we estimate firm-level productivity by employing the Ackerberg, Caves, and Frazer (2015) method that explicitly controls for the potential bias.[9]

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 intermediate inputs that an individual firm purchased from its upstream foreign subsidiaries. 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. Finally we apply 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 average distance between a Chinese domestic firm and its foreign intermediate inputs suppliers defined in Eq. (6) to measure this Chinese domestic firm's accessibility to FDI intermediate inputs. Firm location (at the district level) is documented in our data, which enables us to calculate the distance between any two firms.

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 six-digit district code that reflects all three tiers. Specifically, the first two digits of a district code refer to the province, the middle two digits indicate the city, and the last two digits identify the district.[10] 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 two locations.[11] Ideally, one may expect to measure the actual distance between any two districts through highways, country roads, or railroads. However,

[9] Specifically, the time-varying component of firm technology ζ_{ht} evolves according to a first-order Markov process. As ζ_{ht} affects firm h to determine its real intermediate input expenditure, the real intermediate input expenditure contains information of ζ_{ht} and therefore can be used as a proxy. Employing this fact, we regress the output of firm h on its capital, labor, and real intermediate input expenditure. The regression results can be used to construct the innovation in ζ_{ht} in the Markov process. Then, two moment conditions arise: the innovation of ζ_{ht} is independent of capital and labor choices in the last period. These two moment conditions pin down the parameters for labor and capital in the production function.

[10] 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.

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

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 a Chinese domestic firm h in industry i and FDI firms 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 mean of the distances for this upstream industry j. We repeat this mean distance calculation for all upstream industries. Finally, we calculate the weighted average of the mean distances between firm h and FDI firms in each upstream industry, where weights are from the input-output matrix of China.

3.2 *Summary statistics*

We present the summary statistics in table 1. In panel A, the mean of the log measured total factor productivity on average is 3.318 with the standard deviation 1.407 during our data time span. $Forward$, the upstream FDI intermediate input share, has increased rapidly from 8.695% in 2000 to 14.268% in 2007.

In panel B, we report the summary statistics of the distance distribution (a domestic firm's average distance to its upstream foreign subsidiaries) with two different geographical scopes—nationwide and within a province. A firm's average distance to all upstream FDI firms in China between 2000 and 2007 is 332.357 kilometers. There are some variations in the average distances to nationwide upstream foreign subsidiaries across years due to entry and exit of multinational firms. The standard deviation of the distance distribution has been increasing in the time span, indicating that FDI firms have been more graphically spread out in China. Similarly, a firm's average distance to upstream FDI firms within a province displays a steady growth in the time span of eight years from 44.491 to 53.670 kilometers. The standard deviation of the distance distribution within a province across years also increases, consistent with the pattern in the nationwide scope just with a smaller magnitude. We take the log of the distance statistics for all the empirical analyses in section 4. Given the geographical area of China, these distance statistics are not large in magnitude, which shows the high density of upstream foreign subsidiaries. It is interesting to see whether this small average distance is important enough to affect the accessibility of FDI intermediate inputs, and thus to affect the forward productivity spillover for Chinese domestic firms.

4 Results

4.1 *Benchmark results*

We estimate the benchmark model Eq. (7) by employing the fixed effects panel regressions to remove any unobserved time-invariant heterogeneity. We report the estimations results using the log of nationwide and within-province distance measures in panels A and B respectively, of table 2.

In panel A (table 2), column 1 presents the benchmark regression (7) with the upstream industry concentration index $HHIF$ as the control variable, reported as $Forward\ HHI$. The existence of foreign subsidiaries may increase the toughness of competition and consequently improve the overall efficiency in upstream industries. Although the benefit from an increase in the competition of upstream industries due to the entry of FDI firms can be viewed as part of the generalized spillover effect, we control for this effect in order to target on the spillover through the accessibility of intermediate inputs produced by foreign subsidiaries. Specifically, we calculate the Herfindahl-Hirschman index (HHI_{jt}) as the sum of the squared market shares of the 50 largest firms in an upstream industry j for year t. The degree of concentration of upstream industries faced by any firm in industry i is $HHIF_{it} = \sum_j \alpha_{ji} HHI_{jt}$.

Besides the time-varying concentration ratio of upstream industries, the measured productivity of Chinese domestic firms may also be influenced by time-varying local factors, such as regional demand and supply shocks, development in infrastructure, improvement in scientific research, and openness of trade. Following Sun et al. (2002) and Chen and Moore (2010), in column 2 we add real GDP for market supply, real GDP per capita and retail sale for market demand, railroad per km^2 and road per km^2 for infrastructure development, the number of scientists per thousand persons for research and development, and ratios of import and export over GDP for openness at the province-time level.[12] We also control for the industry-time level variable HHI_{it} and firm-time level variables log of the firm age and capital labor ratio.

The coefficients of $Forward$ and its interaction with the firm-level distance statistics in columns 1 and 2 of panel A 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). Specifically, as in column 2, if a Chinese domestic firm's upstream FDI intermediate input share increases by 1 percentage point, the productivity of this firm will increase by 2.8%. In addition, if this firm is 1% geographically remoter to its upstream FDI firms (on average 3 kilometers) at the national level,[13] its productivity is on average 0.06% lower than an otherwise identical firm.[14]

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 — east, central, and west.[15] The east region has embraced greater openness to the world and experienced faster growth; central and west regions, due to their geographic disadvantages and historical conservativeness, have grown slowly.

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

[13] 1% geographically closer according to the nationwide distance statistics means approximately 3 kilometers closer on average, or ranging between 0.5 and 6 kilometers within two standard deviations.

[14] 0.06%=0.005*12*1%, where the average value of $Forward$ is approximately 12 percentage points in the sample.

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

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. Columns 3-5 in panel A of table 2 present the estimations for the productivity spillovers for these three economic regions. The results for different regions are qualitatively consistent with the benchmark results. It is not surprising to see that both the general productivity-enhancing effect and the proximity effect are larger for firms located in the east economic region.

In panel B of table 2, we employ a different measure of distance statistics—the weighted mean distance between the domestic firm and upstream FDI firms within the same province. We postulate that market frictions may limit most Chinese domestic firms to use FDI intermediate inputs within the same province, instead of all over the country. Moreover, technology diffusions associated with intermediate inputs may also be restricted by the provincial borders due to high communication costs. Panel B displays the estimation results for whether adding control variables (columns 1 and 2) and robustness checks in the subsamples of the east, central, and west regions (columns 3 to 5). All results are consistent with the benchmark results—within a province, Chinese domestic firms can gain higher productivity through the channels of (i) larger upstream FDI share (general productivity-enhancing effect) and (ii) closer distance to upstream FDI firms (proximity effect).

4.2 *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 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[16] 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 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 invest-

[16]Data resource: National Bureau of Statistics of China.

ment 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 wave 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 resold 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.[17] 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 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 3 presents the robustness checks after controlling for labor market and capital-good market externalities. We control for the labor market externality at the city-time level, employing nationwide and within-province distance statistics respectively in columns 1 and 2. Columns 3 and 4 control for the capital-good market externality; and columns 5 and 6 include both externalities. 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 mar-

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

kets. Besides these channels, the benchmark results are robust both qualitatively and quantitatively.

4.3 *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.[18] Then we apply the input usage shares from China's input-output table to generate the upstream aggregate domestic productivity.

Table 4 reports the estimation results that include the upstream aggregate domestic productivity as the control variable. The first three specifications use the nationwide distance statistics, and the latter three employ the within-province distance statistics. We gradually add more control variables in addition to the the upstream aggregate domestic productivity from specifications (1) to (3), and from specifications (4) to (6). The coefficients of the upstream aggregate domestic productivity for all specifications are positive and significant with very similar magnitudes, indicating 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 proximity effect from FDI intermediate inputs do not change at all; in addition, the general productivity-enhancing effect from upstream FDI firms is even larger in magnitude.

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

4.4 *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.[19]

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

All regression specifications in table 5 control for both FDI horizontal and backward spillover channels. Specifications (1) to (3) use the nationwide distance statistics, and (4) to (6) employ the within-province distance statistics. Again we gradually add more controls from (1) to (3), and from (4) to (6). Consistent with the literature, the FDI horizontal spillover effects are mostly negative unless we control for the upstream aggregate domestic productivity, while the backward spillover

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

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.

4.5 *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, 25% of firms used imported intermediate inputs during 2000 and 2007. Among them, 66% of foreign firms and 12.5% of domestic firms have imported 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 benchmark regressions. The estimation results are shown in table 6. Different from Halpern et al. (2015), imported intermediate inputs do not benefit Chinese firms in their productivity, and this is very 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 very robust in both statistical significance and economic magnitude.

4.6 *The endogenous location choice by firms*

4.6.1 *The endogenous location choice by domestic firms*

If the proximity effect does hold, it is possible that productive Chinese domestic firms self-select their locations to be close to their upstream FDI suppliers. And thus, our proximity effect in the benchmark estimation may be biased upward. 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.

Table 7 reports the estimation results based on this subsample with observations reduced to two thirds of the original data. Columns (1) to (3) use the nationwide distance statistics, and (4) to (6) employ the within-province distance statistics. Compared to the benchmark results, there is almost no change in the general productivity-enhancing effect and the magnitude of the proximity effect only decreases a little for the within-province specifications.

4.6.2 *The endogenous location choice by FDI firms*

Multinational firms may also choose the optimal locations to establish their foreign affiliates. Foreign affiliates are very likely to cluster in some locations, and therefore the distance statistics from FDI firms are smaller for the Chinese firms in these locations. The determinants of location choice—for example, a large local market size or good infrastructures—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 regression.

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 six-digit district code level) and 0 otherwise. According to Cheng and Kwan (2000), 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%.[20] 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.[21]

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.[22] The random effects probit model is

$$Pr(P_{rt} = 1) = \Phi(a + B_1 X_{pt} + B_2 X_{rt} + \epsilon_{rt}), \tag{8}$$

[20] 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).

[21] 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*.

[22] 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).

where Φ is the cumulative normal distribution, a 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.

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 benchmark fixed effects panel regression Eq. (7) by matching each firm's location with the six-digit district r.

Table 8 displays the estimation results after controlling for the FDI endogenous choice. 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,[23] 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 coefficients for the predicted FDI location probability in all four specifications are significantly positive. That is, if a Chinese domestic firm locates in an area preferred by FDI firms, it enjoys higher productivity. More importantly, the general productivity-enhancing effect and the proximity effect in all four specifications are qualitatively unchanged from our benchmark estimations after we control for the endogenous FDI location choice.

5 Conclusion

This paper provides the supporting evidence that positive productivity spillovers are transmitted from upstream FDI firms to domestic firms through the channel of intermediate inputs. We model and empirically confirm the gravity of intermediate inputs—not only the relative contribution of FDI in upstream industries, but also the heterogenous distance distributions between domestic firms and upstream FDI firms affect the productivity spillovers. These findings further suggest that if policymakers want domestic firms to absorb productivity spillovers from FDI firms more

[23]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.

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.

Table 1: Summary Statistics

Panel A: Productivity and spillover variables

Year	Number of local	ln(TFP)		Forward (%)	
	firm-year observations	Mean	Standard deviation	Mean	Standard deviation
2000	68,825	2.816	1.530	8.695	3.001
2001	71,618	2.886	1.448	8.781	3.059
2002	68,183	3.017	1.454	9.935	3.298
2003	68,037	3.196	1.387	11.658	4.889
2004	82,262	3.316	1.320	13.211	5.289
2005	78,543	3.511	1.313	13.658	6.015
2006	83,336	3.659	1.278	14.166	5.833
2007	93,760	3.861	1.211	14.268	5.929
Total	614,564	3.318	1.407	12.002	5.402

Panel B: A firm's distance distribution to upstream FDI firms

Year	Number of local	Nationwide (km)		Within-province (km)	
	firm-year observations	Mean	Standard deviation	Mean	Standard deviation
2000	68,825	322.693	140.801	44.491	19.909
2001	71,618	315.399	145.368	43.791	19.723
2002	68,183	319.178	145.628	44.155	19.625
2003	68,037	346.357	159.427	48.117	21.828
2004	82,262	337.689	161.022	48.970	23.254
2005	78,543	340.930	160.731	50.883	23.774
2006	83,336	339.057	160.683	52.008	24.545
2007	93,760	333.997	158.744	53.670	24.965
Total	614,564	332.357	154.618	48.610	22.410

Note: ln(TFP) is firm-level measured productivity, Forward is the portion of domestic sales contributed by foreign capital in upstream industries. A firm's distance distribution to upstream FDI firms can be computed as weighted mean distances between the firm and all FDI firms in China (nationwide), or between the firm and FDI firms in the same province (within-province).

Table 2: Benchmark Results

Panel A Fixed effects panel regressions: Nationwide

Dependent variable:	All	All	East	Central	West
ln(TFP)	(1)	(2)	(3)	(4)	(5)
Forward	0.011**	0.028***	0.031***	−0.002	0.035*
	(0.005)	(0.005)	(0.007)	(0.013)	(0.020)
ln(Distance statistic) * Forward	−0.002**	−0.005***	−0.006***	0.001	−0.006*
	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
Forward HHI	−0.0005***	−0.0005***	−0.0006***	−0.0001	−0.0010**
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
Other control v.	No	Yes	Yes	Yes	Yes
R^2	0.296	0.271	0.247	0.334	0.306
$N.of firms$	239,993	239,855	157,905	56,425	25,530
N	614,564	613,606	395,348	144,190	74,068

Panel B Fixed effects panel regressions: Within-province

Dependent variable:	All	All	East	Central	West
ln(TFP)	(1)	(2)	(3)	(4)	(5)
Forward	0.003***	0.003***	0.003***	0.005***	0.001
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ln(Distance statistic) * Forward	−0.199***	−0.065***	−0.092***	−0.059	0.233**
	(0.017)	(0.019)	(0.023)	(0.047)	(0.099)
Forward HHI	−0.0005***	−0.0005***	−0.0005***	−0.0001	−0.0008**
	(0.0001)	(0.0001)	(0.0002)	(0.0003)	(0.0004)
Other control v.	No	Yes	Yes	Yes	Yes
R^2	0.290	0.269	0.246	0.334	0.305
$N.of firms$	239,993	239,855	157,905	56,425	25,530
N	614,564	613,606	395,348	144,190	74,068

Note: Distance statistic refers to a firm's weighted mean distance to its upstream FDI firms. Forward HHI is the Herfindahl-Hirschman index for upstream industries. Other control variables include HHI at the industry-time level, real GDP, real GDP per capita, retail sale, railroad per km^2, road per km^2, the number of R&D scientists per thousand persons, ratios of import and export over GDP at the province-time level, log of firm age and capital labor ratio at the firm-time level. East area includes Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; central area includes Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; west area includes Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Gansu, Shaanxi, Qinghai, Ningxia, and Xinjiang. All other variables are defined in table 1. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 3: Labor Market and Capital-good Market Externality

Fixed effects panel regressions

	Labor		Capital-good		Both	
Dependent variable:	Nationwide	Within-province	Nationwide	Within-province	Nationwide	Within-province
ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Forward	0.030^{***}	0.003^{***}	0.029^{**}	0.003^{***}	0.030^{***}	0.003^{***}
	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
ln(Distance statistic) * Forward	-0.005^{***}	-0.067^{***}	-0.005^{***}	-0.069^{***}	-0.005^{***}	-0.069^{***}
	(0.001)	(0.019)	(0.001)	(0.019)	(0.001)	(0.019)
Forward HHI	-0.0004^{***}	-0.0003^{**}	-0.0005^{***}	-0.0004^{***}	-0.0004^{***}	-0.0003^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Labor market externality	0.198^{***}	0.193^{***}			0.155^{***}	0.150^{***}
	(0.020)	(0.020)			(0.023)	(0.023)
Capital-good market externality			0.261^{***}	0.256^{***}	0.146^{***}	0.144^{***}
			(0.032)	(0.032)	(0.036)	(0.036)
Other control v.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.273	0.270	0.272	0.270	0.273	0.270
$N.of firms$	239,855	239,855	239,855	239,855	239,855	239,855
N	613,606	613,606	613,606	613,606	613,606	613,606

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. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 4: Upstream Aggregate Domestic Productivity

Fixed effects panel regressions

Dependent variable:	Nationwide			Within-province		
ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Forward	0.024^{***}	0.048^{***}	0.049^{***}	0.006^{***}	0.008^{***}	0.007^{***}
	(0.005)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
ln(Distance statistic) * Forward	-0.004^{***}	-0.007^{***}	-0.008^{***}	-0.120^{***}	-0.064^{***}	-0.067^{***}
	(0.001)	(0.001)	(0.001)	(0.017)	(0.019)	(0.019)
Forward HHI	-0.0007^{***}	-0.0008^{***}	-0.0007^{***}	-0.0007^{***}	-0.0006^{***}	-0.0005^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Upstream AGGR domestic productivity	0.221^{***}	0.323^{***}	0.295^{***}	0.205^{***}	0.286^{***}	0.257^{***}
	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)	(0.024)
Other control v.	No	Yes	Yes	No	Yes	Yes
L and K markets externality controls	No	No	Yes	No	No	Yes
R^2	0.297	0.271	0.272	0.290	0.268	0.269
$N.of firms$	239,993	239,855	239,855	239,993	239,855	239,855
N	614,564	613,606	613,606	614,564	613,606	613,606

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 to 3. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 5: Other FDI Spillover Channels

Fixed effects panel regressions

Dependent variable:	Nationwide			Within-province		
ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Forward	0.009*	0.030***	0.047***	0.001	0.003***	0.005***
	(0.005)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
ln(Distance statistic) * Forward	−0.002**	−0.005***	−0.007***	−0.202***	−0.066***	−0.074***
	(0.001)	(0.001)	(0.001)	(0.018)	(0.019)	(0.019)
Forward HHI	−0.0005***	−0.0006***	−0.0007***	−0.0005***	−0.0005***	−0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Horizontal	−0.0009	−0.0010	0.0015**	0.0017**	−0.0003	0.0025***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Backward	0.0000	0.0002*	0.0002	0.0000	0.0002*	0.0002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Other control v.	No	Yes	Yes	No	Yes	Yes
L and K markets externality controls	No	No	Yes	No	No	Yes
Upstream AGGR domestic productivity	No	No	Yes	No	No	Yes
R^2	0.296	0.271	0.272	0.290	0.269	0.269
$N.of firms$	239,993	239,855	239,855	239,993	239,855	239,855
N	614,564	613,606	613,606	614,564	613,606	613,606

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 to 4. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 6: Imported Intermediate Inputs

Fixed effects panel regressions

Dependent variable:	Nationwide			Within-province		
ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Forward	0.011^{**}	0.028^{***}	0.047^{***}	0.003^{***}	0.003^{***}	0.005^{***}
	(0.005)	(0.005)	(0.006)	(0.001)	(0.001)	(0.001)
ln(Distance statistic) * Forward	-0.002^{**}	-0.005^{***}	-0.007^{***}	-0.198^{***}	-0.065^{*}	-0.073^{**}
	(0.001)	(0.001)	(0.001)	(0.017)	(0.019)	(0.019)
Forward HHI	-0.0005^{***}	-0.0005^{***}	-0.0007^{***}	-0.0005^{***}	-0.0005^{***}	-0.0005^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Imported Input Ratio	-0.849^{***}	-0.843^{***}	-0.850^{***}	-0.840^{***}	-0.837^{***}	-0.839^{***}
	(0.132)	(0.131)	(0.131)	(0.132)	(0.131)	(0.131)
Other control v.	No	Yes	Yes	No	Yes	Yes
L and K markets externality controls	No	No	Yes	No	No	Yes
Upstream AGGR domestic productivity	No	No	Yes	No	No	Yes
Horizontal and Backward	No	No	Yes	No	No	Yes
R^2	0.296	0.271	0.272	0.290	0.269	0.269
$N.of firms$	239,993	239,855	239,855	239,993	239,855	239,855
N	614,564	613,606	613,606	614,564	613,606	613,606

Note: Imported input ratio is the total value of imported products over that of production. All other variables are defined in tables 1 to 5. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 7: The Endogenous Location Choice of Domestic Firms

Fixed effects panel regressions

Dependent variable:	Nationwide			Within-province		
ln(TFP)	(1)	(2)	(3)	(4)	(5)	(6)
Forward	0.010^{*}	0.024^{***}	0.042^{***}	0.004^{***}	0.004^{***}	0.006^{***}
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
ln(Distance statistic) * Forward	-0.002^{*}	-0.004^{***}	-0.006^{***}	-0.162^{***}	-0.042^{**}	-0.050^{**}
	(0.001)	(0.001)	(0.001)	(0.019)	(0.021)	(0.021)
Forward HHI	-0.0006^{***}	-0.0005^{***}	-0.0007^{***}	-0.0006^{***}	-0.0005^{***}	-0.0006^{***}
	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Other control v.	No	Yes	Yes	No	Yes	Yes
L and K markets externality controls	No	No	Yes	No	No	Yes
Upstream AGGR domestic productivity	No	No	Yes	No	No	Yes
Horizontal and Backward	No	No	Yes	No	No	Yes
R^2	0.291	0.280	0.281	0.285	0.278	0.278
$N.of firms$	150,127	150,057	150,057	150,127	150,057	150,057
N	426,273	425,799	425,799	426,273	425,799	425,799

Note: We only include domestic firms that have start year earlier than 2000. All other variables are defined in tables 1 to 5. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

Table 8: The Endogenous Location Choice of FDI Firms

Dependent variable: FDI locating probability		Dependent variable: ln(TFP)	Nationwide (1)	(2)	Within-province (3)	(4)
ln(Market potential)	4.183***	Forward	0.036***	0.057***	0.003***	0.005***
	(0.154)		(0.005)	(0.006)	(0.001)	(0.001)
ln(Labor cost)	−0.362**	ln(Distance statistic) * Forward	−0.006***	−0.009***	−0.050***	−0.059***
	(0.168)		(0.001)	(0.001)	(0.018)	(0.019)
Economic and tech.	4.956***	Forward HHI	−0.0006***	−0.0007***	−0.0005***	−0.0005***
development zone	(0.869)		(0.0001)	(0.0001)	(0.0001)	(0.0001)
		FDI locating probability	0.356***	0.374***	0.323***	0.326***
			(0.031)	(0.031)	(0.031)	(0.031)
		Other control v.	Yes	Yes	Yes	Yes
		L/K markets externality	No	Yes	No	Yes
		Upstream AGGR domestic productivity	No	Yes	No	Yes
		Horizontal and Backword	No	Yes	No	Yes
$Psudo\ R^2$	0.068	R^2	0.284	0.284	0.282	0.281
$N.of districts$	3,209	$N.of firms$	239,843	239,843	239,843	239,843
N	21,447	N	613,476	613,476	613,476	613,476

Note: The first stage regression employs the random effects 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 provincial 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, except the fitted FDI locating probability, all other variables are defined in tables 1 to 5. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

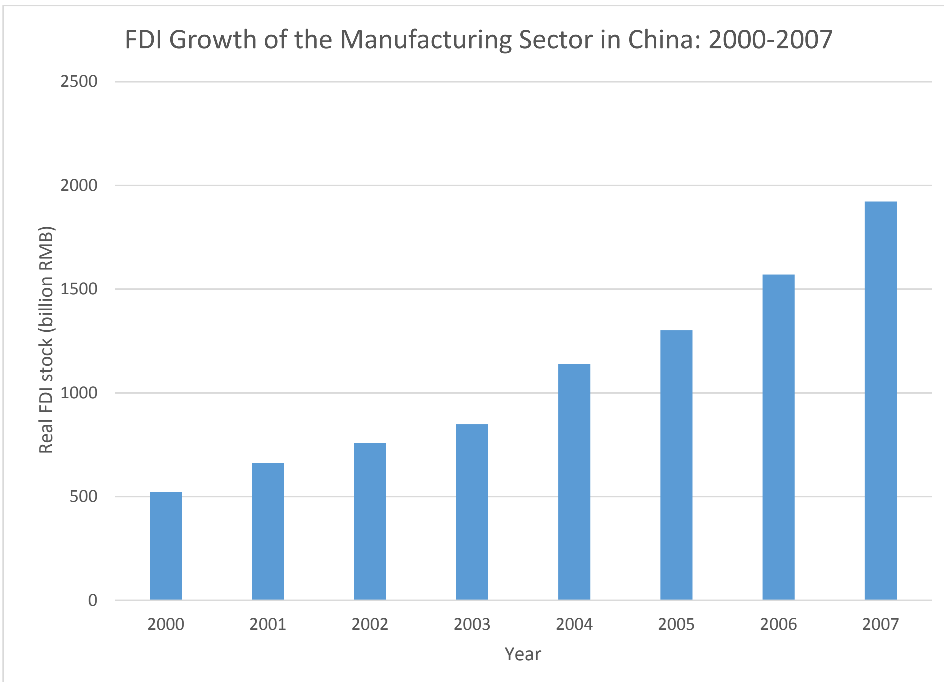

Fig. 1: FDI Growth of the Manufacturing Factor in China

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: 1999).

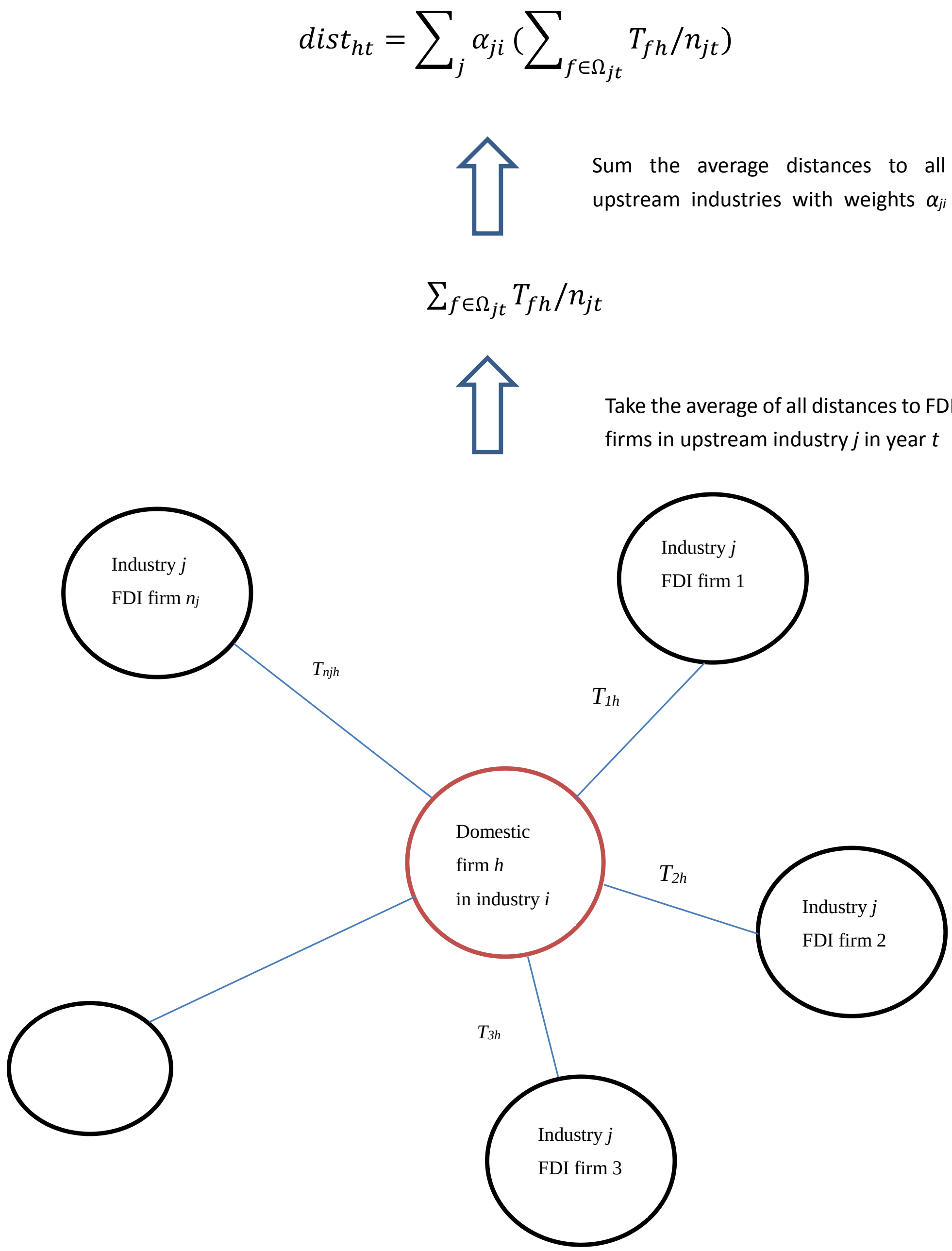

Fig. 2: A Firm's Distance Distribution

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Appendix

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

$$y^{va}_{hit} = \gamma_k k_{hit} + \gamma_l l_{hit} + a_{hit} + \epsilon_{hit}, \tag{9}$$

where y, k and l stand for the logarithm of value-added output, 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. 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^r_{hit} in period t. We write the choice of the intermediate input as

$$m^r_{hit} = f_t(k_{hit}, l_{hit}, a_{hit}). \tag{10}$$

Substituting (10) to (9) yields

$$y^{va}_{hit} = \gamma_k k_{hit} + \gamma_l l_{hit} + f_t^{-1}(k_{hit}, l_{hit}, m^r_{hit}) + \epsilon_{hit}. \tag{11}$$

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

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

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

In the third step, we find two independent moment conditions in order to identify γ_k and γ_l. First, if k_{hit} is determined one period ahead and hence $k_{hit} \in I_{hit-1}$, it should be independent of the productivity innovation ξ_{hit}, i.e., $E[\xi_{hit}|k_{hit}] = 0$. Another condition uses the independence between labor l_{hit} and ξ_{hit} because l_{hit} is determined one period ahead: $E[\xi_{hit}|l_{hit}] = 0$. In summary, two conditions imply

$$E[\xi_{hit} \begin{pmatrix} k_{hit} \\ l_{hit} \end{pmatrix}] = 0. \tag{12}$$

We then estimate γ_k and γ_l by employing these two moment conditions in (12). 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 (12):

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

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

The three-step procedure yields $\hat{a}_{hit}$, the estimation of firm i's productivity in industry i. We repeat the procedure and compute the observed total factor productivity for every industry.