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

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November 14, 2016

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Abstract

We develop a partial equilibrium model to illustrate that upstream foreign direct investment (FDI) generates heterogeneous productivity spillovers to downstream domestic firms through the gravity of intermediate inputs. Our model predicts that a domestic firm enjoys a higher productivity if it can get access to more intermediate inputs sold by FDI firms (general productivity-enhancing effect) and it is geographically closer to its upstream FDI firms (proximity effect). We use Chinese firm-level data from 2000 to 2007 to empirically identify these two tiers of productivity spillover effects. 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%. And if this firm is 1% geographically closer to its upstream FDI firms (on average 3 kilometers), its productivity is 0.06% higher than an otherwise identical firm. The results are robust qualitatively and quantitatively after we control for the labor and capital-good market externalities, the upstream aggregate domestic productivity, other potential FDI spillover channels, and the endogenous FDI location choice.

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

Keywords: FDI, productivity spillover, gravity effect, economic geography, China

1 Introduction

Foreign direct investment (FDI) has been surging into developing countries and emerging markets since 1990s. The net inflows of FDI to low and middle income countries in 2015 are approximately 22.20 times more than the net FDI inflows to these countries in 1991.[1] Take a specific country China as an example, the total subscribed foreign capital in Chinese manufacturing firms—the measure of FDI stock at the firm level—has more than tripled between 2000 and 2007, as shown in figure 1. The rapid growth of FDI into emerging markets is closely associated with the consistent FDI stimulating policies such as tax reductions and entry subsidies, because policy makers usually believe that FDI not only provides a risk bumper that helps to mitigate the business cycle volatility,[2] but also infuses advanced technology and generates positive externality to domestic firms.

Different from the conventional wisdom and policy makers' belief, an extensive literature presents mixed evidence on the productivity spillovers of FDI toward domestic firms through a variety of channels.[3] Due to data availability, previous empirical papers in this trend of literature focus on the homogenous impacts of FDI productivity spillovers toward 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 in a differentiated way in reality. As a result, policy makers need to design more targeted policies that align domestic firms with more appropriate differentiated incentives to better absorb productivity spillovers. The mixed evidence on FDI productivity spillovers and limited understandings on spillover heterogeneity necessitate further investigations.

Our paper aims to explore one of the channels of FDI productivity spillovers—the forward productivity spillover channel, and the heterogeneous impacts of spillovers on domestic firms. We

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

[2] See Aguiar and Gopinath (2005).

[3] 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), and Fons-Rosen et al. (2013) find no evidence of positive productivity spillovers from FDI firms.

find that the gravity of intermediate inputs exists in productivity spillovers from upstream FDI firms to downstream domestic firms. We model and identify the gravity of intermediate inputs in productivity spillovers by decomposing it into a general productivity-enhancing effect homogeneous to all downstream domestic firms in a given industry, and a proximity effect that depends on the heterogeneous distance distribution between domestic and upstream FDI firms. A domestic firm can gain more in its productivity if it can get access to more upstream FDI intermediate inputs and if it is geographically closer to upstream FDI firms.

Intermediate inputs produced by more productive multinational firms (Helpman, Melitz and Yeaple, 2004) are believed to embody more advanced technology (Keller and Yeaple, 2013). When host-country domestic firms acquire intermediate inputs produced by FDI firms in their upstream industries, the more cost-efficient intermediate inputs and the associated technical supports could generate positive externality to these domestic firms. This homogenous productivity spillover to domestic firms from the overall existence of upstream FDI is defined as the general productivity-enhancing effect in this paper. We offer a theoretical explanation for the underlying mechanism—intermediate inputs—of this effect, and show that if a Chinese domestic firm's upstream FDI input share increases by 1 percentage point, the productivity of this firm will increase by 2.8%.

In addition to the general productivity-enhancing effect, domestic firms may be heterogeneously impacted by upstream FDI firms if they have different geographical distance distributions to upstream FDI firms, which is called the proximity effect in this paper. Previous FDI literature has discussed how the geographical distance distribution affect FDI spillovers (Keller, 2002), and the spatial interdependence of FDI flows (Blonigen et al., 2007). Comin et al. (2012) theoretically explains how the geographical remoteness between technology adopters and developers impedes technology diffusion and finds empirical evidence at the country level. We consider firm-level differentiated iceberg costs for the purchase of FDI intermediate inputs in the theoretical model, and empirically find that if a Chinese domestic firm is 1% geographically remoter to its upstream FDI firms (on average 3 kilometers), its productivity is 0.06% lower.

This paper constructs a multi-sector heterogeneous firm model, in which domestic firms have access to all upstream FDI intermediate inputs. Similar to imported inputs in the literature (Goldberg et al., 2010, Amiti, et al., 2014, and Halpern el al., 2015), intermediate inputs produced by upstream FDI firms have a productivity-enhancing advantage in comparison to domestic intermediate inputs. However, employing FDI inputs also incurs procurement costs that are positively correlated with distances between upstream FDI firms and downstream domestic firms. When a domestic firms minimizes its total cost, the total factor productivity of this firm consists of three components—the individual technology parameter, the general productivity enhancing effect of FDI intermediate inputs, and the proximity effect related to the distance distribution from its upstream FDI firms. Any exogenous change in the last two components affects the productivity spillovers toward a domestic firm.

We construct a benchmark estimation equation based on the theory. If the contribution of FDI in upstream industries increases, either due to a larger portion of subscribed foreign capital, or due to more domestic sales by FDI firms, the general productivity-enhancing effect will be fortified. Moreover, with China's accession to the World Trade Organization (WTO), the entry and exit of upstream FDI firms change the distance distribution to any domestic firm and therefore alter the productivity spillover through the proximity effect.

We use the Chinese firm-level data between 2000 and 2007 to test these two effects to prove the gravity of intermediate inputs. China has a relatively complete industrial structure and benefits from producing and exporting goods in a variety of industries[4]; therefore China is an ideal natural experimental field to examine spillovers through industrial links. We measure the relative contribution of upstream FDI as the average portion of FDI intermediate inputs from upstream industries weighted by the Chinese input-output matrix parameters. We further calculate the summary statistics of the distance distribution for each domestic firm as the weighted sum of average

[4]Hausmann et al. (2007) and Jarreau and Poncet (2012) show that a country that produces and exports more sophisticated goods enjoys higher economic growth.

distances between the domestic firm and FDI firms in each upstream industry, again weighted by the Chinese input-output matrix parameters. We calculate two sets of distance summary statistics for each domestic firm—the weighted mean distance between the domestic firm and all upstream FDI firms in China and between the domestic firm and upstream FDI firms in the same province. We apply the fixed-effects panel regression to estimate the benchmark estimation equation. The estimation results provide supporting evidence that both the general productivity-enhancing effect and the proximity effect exist—domestic firms that are exposed to more FDI intermediate inputs and/or geographically closer to upstream FDI firms benefit more from productivity spillovers.

Our empirical results are robust to i) two measures of distance statistics—nationwide and within the province, and ii) sub-samples of east, central, and west regions. Moreover, after we control for the potential local labor and capital-good markets externalities (Ellison et al., 2010), upstream domestic firms' spillovers, FDI productivity spillovers from the same and downstream industries (Javorcik, 2004, Liu, 2008), and the endogeneity of firm location choice (Cheng and Kwan, 2000, Amiti and Javorcik, 2008, and Chen and Moore, 2010), the coefficients for the general productivity-enhancing effect and the proximity effect are still qualitatively and quantitatively unchanged.

This paper first contributes to the literature by rationalizing the underlying mechanism of productivity spillovers from upstream FDI firms with the gravity of intermediate inputs. Our model decomposes the gravity of intermediate inputs in productivity spillovers into two tiers. The first tier is the general productivity-enhancing effect homogeneous to all domestic firms in a given industry, which corresponds to the "forward linkage" of FDI spillover effects. This effect is widely studied such as in Javorcik (2004), Liu (2008), and Gorodnichenko et al. (2014), but not well modeled. Second, our paper extends the imported inputs literature (Goldberg et al., 2010, Amiti, et al., 2014, and Halpern el al., 2015) to the FDI intermediate inputs, and explains that the general productivity-enhancing effect arises because of the more cost-efficient FDI intermediate inputs. The second tier is the proximity effect heterogeneous to domestic firms in a given industry. We theoretically model how the variations in the distance distribution between upstream FDI firms and downstream domestic firms affect the productivity spillovers, construct a set of unique firm-level distance statistics with the Chinese firm-level data, and find strong empirical supports. The proximity effect also enriches the literature on the spatial effects of FDI (Keller, 2002, Comin et al., 2012) to firm-level microanalysis.

The remainder of the paper is organized as follows. Section 2 builds an illustrative model that explicitly describes that FDI in upstream industries augments domestic firms' productivity through the gravity of intermediate inputs and then propose the benchmark estimation equation. Section 3 describes the data and constructs 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 heterogenous firms. This model allows us to analyze how the technological advantage of intermediate inputs produced by upstream FDI firms affects Chinese domestic firms' productivity, and how the productivity spillover effects vary with domestic firms' geographical accessibility to upstream FDI firms. We then propose the benchmark estimation equation according to this multi-sector production model.

2.1 The illustrative model

There are a large number of firms producing in a market. Each firm, heterogeneous in productivity, needs to purchase intermediate inputs from firms in other industries besides using the primary inputs — labor and capital. This multi-sector production model describes a partial equilibrium in which firms minimize production costs.

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—produces a differentiated variety and differs in productivity 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:

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

where γ_k, γ_l, and γ_x measure the shares of capital, labor, and intermediate inputs respectively. These shares are industry-specific and identical to all firms in the same industry. To make notations parsimoniously, we leave the industry subscript off the share parameters.

We assume that both primary inputs (capital and labor) are homogeneous and firm h can acquire them in perfectly competitive markets. This assumption reduces firm h's cost minimization problem to choosing its optimal combination of intermediate inputs.

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 purchased by industry i from upstream industry j, and C_{i1} is a constant: $C_{i1} = \prod_j \alpha_{ji}^{\alpha_{ji}}$.

The intermediate input from industry j, X_{ji}, can further be decomposed to two varieties produced by domestic and FDI firms: X_{Dj} and X_{Fj}. Domestic and FDI intermediate inputs 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 κ_i is the share of FDI intermediate inputs and identical for all firms in industry i; C_{i2} is a constant: $C_{i2} = (1-\kappa_i)^{1-\kappa_i}\kappa_i^{\kappa_i}$; η measures the productivity-enhancing effect of FDI intermediate inputs, and $\eta > 1$.[5] We assume the technological advantage parameter η to be constant for all firms and industries. Keller and Yeaple (2013), Amiti, et al. (2014), and Halpern, et al. (2015) document and model that imported inputs can enhance the productivity of domestic firms because these inputs contain more advanced knowledge and/or have better quality, and thus they are more effective inputs during the production process for any downstream firm. Consistent with these papers, we assume that similar to imported inputs, FDI intermediate inputs can also improve the productivity of downstream domestic firms and the productivity-enhancing effect of FDI intermediate inputs is summarized by the parameter η.

In order to focus on examining the impacts of FDI intermediate inputs, we simplify the structure of domestic intermediate inputs by assuming that intermediate inputs from upstream domestic firms in industry j are perfect substitutes[6]; therefore, firm h only purchases from the geographically closest upstream firm to minimize transportation costs. Intermediate inputs provided by different upstream FDI firms in industry j are imperfectly substitutable, so that 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 in industry j, and $C_{Fj} = \prod \omega_j^{\omega_j}$ is a constant for the purpose of normalization. Note that we have to assume firm h purchases intermediate inputs from all upstream FDI firms since no firm-level input-output matrix is available in our data.[7] Therefore, similar to Amiti and Javorcik (2008) in which the authors use "supplier access" to measure an individual firm's input choice set,

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

[6] To rationalize the perfect substitutability of domestic intermediate inputs, one may assume that domestic intermediate inputs are homogeneous.

[7] Alternatively, we can assume that there is no fixed cost to purchase FDI intermediate inputs; therefore, a firm can purchase intermediate inputs from all upstream FDI firms, similar to the firm choice problem in Keller and Yeaple (2013) and Halpern, et al. (2015).

later we will demonstrate how changes in upstream FDI firms' intermediate input supplies would affect downstream domestic firms.

The intermediate input price index According to the structure of intermediate inputs we have assumed, firm h determines its expenditure M_h on intermediate inputs X_h. Both domestic and FDI firms in industry j sell inputs at P_j. There is an iceberg cost if firm h purchases intermediate inputs from FDI firm f located in a separate place; and we use the distance between two firms T_{fh} to be the proxy of this iceberg cost. Then the price index for industry-j FDI intermediate inputs is

$$P_{Fj} = P_j \eta^{-1} G_{jh}, \;\; G_{jh} \equiv \prod_{f \in \Omega_j} \left(e^{T_{fh}} \right)^{\omega_j},$$

where G_{jh} represents the aggregate iceberg cost of industry j for firm h, which is a function of the distance distribution between firm h and upstream FDI firms in industry j. Following Keller (2002), we employ an exponential function form to describe the monotonic relationship between the distance distribution and the iceberg cost. Note that as in Ellison et al. (2010), distance T_{fh} is not only a proxy of transportation costs, it may also reflect technology diffusion costs that surge with distance.[8] Keller (2002) finds that technology spillovers are localized because spillover benefits deteriorate with geographic distance. Specific to the forward spillover channel, with the purchase of intermediate inputs, domestic firms may obtain complementary services and technical supports from their upstream firms. These technical transfers of disembodied knowledge are also important for the efficient use of FDI intermediate inputs, and thus help to improve domestic firms' productivity besides the knowledge embodied in FDI intermediate inputs. If domestic firms are located far away from upstream multinationals, they will receive face-to-face technical support less frequently and thus are less likely to learn the know-how that could facilitate domestic firms' use of FDI intermediate inputs.

[8] In a different model setup, we assume that (i) the iceberg transportation cost increases with $e^{0.5T_{fh}}$; (ii) the productivity enhancing effect of X_{fh} is weakened by the distance between two firms: $\eta / e^{0.5T_{fh}}$. The price index of P_{Fj} does not change under this alternative setup that incorporates multiple roles of the distance distribution.

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

$$P_h^x = \prod_j \left(P_j\right)^{\alpha_{ji}} \underbrace{\prod_j \left(\eta^{-\kappa_i}\right)^{\alpha_{ji}}}_{\text{General cost-saving effect}} \underbrace{\prod_j \left((G_{jh})^{\kappa_i}\right)^{\alpha_{ji}}}_{\text{Proximity effect}},$$

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 FDI intermediate inputs enhance domestic firm h's productivity and consequently reduce the intermediate input costs for domestic firm h. A more productive firm can produce more outputs at a given expenditure of intermediate inputs, or equivalently a given amount of outputs with a lower expenditure of intermediate inputs. The second term emphasizes the general cost-saving effect of FDI inputs which is homogeneous to all domestic firms in industry i; the third term focuses on how the cost-saving effect of FDI intermediate inputs may be weakened due to the heterogenous firm-level geographic remoteness to upstream FDI firms.

Production and intermediate input expenditure We can re-write the production function (1) in terms of capital, labor, intermediate input expenditure, and the intermediate input price index:

$$\begin{aligned} Y_h &= A_h \left(K_h\right)^{\gamma_k} \left(L_h\right)^{\gamma_l} \left(M_h / P_h^x\right)^{\gamma_x} \\ &= A_h \left(K_h\right)^{\gamma_k} \left(L_h\right)^{\gamma_l} M_h^{\gamma_x} \left[\prod_j \left(P_j\right)^{\alpha_{ji}}\right]^{-\gamma_x} \left[\prod_j \left(\eta^{-\kappa_i}\right)^{\alpha_{ji}}\right]^{-\gamma_x} \left[\prod_j \left((G_{jh})^{\kappa_i}\right)^{\alpha_{ji}}\right]^{-\gamma_x}. \end{aligned} \tag{2}$$

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. To see this point, 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 $P^x_{ji} = P_{1j}\eta^{-\kappa_i}\xi^{-\kappa_i}(G_{jh})^{\kappa_i}$. Similar to Halpern et al. (2015), we define $\tilde{\eta} \equiv \eta\xi$ as the price-adjusted productivity-enhancing parameter and then 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 employing $\sum_j \alpha_{ji} = 1$:

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

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 Like Halpern et al. (2015), the total factor productivity of firm h is $a_{ht} + \gamma_x\kappa_{it} ln(\eta) - \gamma_x\kappa_{it}\sum_j \alpha_{ji} ln\big(G_{jht}\big)$, where a_{ht} is the technology parameter of firm h; $\gamma_x ln(\eta)\kappa_{it}$, the term in the first brace of Eq. (3), is the general productivity-enhancing effect which describes how domestic firms benefit from upstream industry foreign direct investments;[9] $\gamma_x\kappa_{it}\sum_j \alpha_{ji} ln\big(G_{jht}\big)$ is specified in the second brace in Eq. (3) which shows the proximity effect. It depicts how domestic firms that are geographically closer to upstream FDI firms benefit more from the forward productivity spillover.

The total productivity spillover effects of FDI intermediate inputs are transmitted through

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

the last two terms on the right hand side of Eq. (3).[10] Specifically, given that the productivity-enhancing parameter of FDI intermediate inputs η and the production function parameter γ_x are constant, the general productivity-enhancing effect varies with κ_{it}, the share of FDI intermediate inputs that measures the relative importance of FDI in upstream industries and varies at the industry-time level. This effect is homogeneous for all domestic firms in the same industry. Later we will describe in detail how to measure the share of FDI intermediate inputs κ_{it}.

We assume that the location choice, entry, and exit of upstream FDI firms are exogenous to firm h. And therefore, the proximity effect in Eq. (3) shows that any changes in firm h's distance distribution to upstream FDI firms $\sum_j \alpha_{ji} ln\big(G_{jht}\big)$ will exogenously affect the productivity spillovers to it.[11] We will show how to measure the geographic distance distribution of firm h to upstream FDI firms later in this subsection.

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 we define $m^r_{ht} \equiv m_{ht} - \sum_j \alpha_{ji} p_{jt}$, which is the real intermediate input expenditure of firm h. Like Gopinath and Neiman (2014) and Halpern et al. (2015), we can only observe the industry-level price index of intermediate inputs p_{jt} but not the input price index for individual firms in our data.

The unobservable technology parameter a_{ht} may cause some bias when we estimate γ_k, γ_l, and γ_x, and the bias may ultimately contaminate estimates of the spillover effects. In order to control for the potential bias, we follow Ackerberg et al. (2015) to assume that productivity a_{ht} affects firm h's decision to choose capital, labor, and intermediate inputs; this relationship can be expressed by a reverse function: $a_{ht} = f^{-1}\big(k_{ht}, l_{ht}, m^r_{ht}\big)$. Details of the estimation method can be found in

[10] We assume that the technology parameter a_{ht} is independent of the productivity spillover effects.

[11] We assume that firm h cannot re-locate after it starts production.

the appendix. Note that the productivity spillover effects do not affect firm h to choose factors of production because an individual firm views the spillover effects as exogenous.

Upstream FDI intermediate input share The general productivity-enhancing parameter of FDI intermediate input η is time-invariant. In order to identify η, we need variations in how FDI intermediate inputs augment domestic firms' productivity when more FDI intermediate input are available to them overtime, as in Broda and Weinstein (2006). Adopting the definition of $forward_{it}$ in Javorcik (2004), we measure the upstream FDI intermediate input share (κ_{it}) as the weighted average portion of FDI outputs that sell in the domestic market:

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

where $fshare_{ft}$ is the share of foreign ownership for firm f in period t, and $(Y_{ft} - EX_{ft})$, the difference between total sales and exports, is the domestic sales of firm f; the fraction term as a whole measures the relative importance of FDI in industry j in providing supplies to the domestic market; overall, $forward_{it}$ averages the portions of FDI inputs in all upstream industries, weighted by the input usage ratios α_{ji} from the input-output matrix.[12]

Firm-level accessibility to upstream FDI firms If the share of intermediate inputs purchased by domestic firm h from FDI firm f in industry j is $\omega_{jt} = 1/n_{jt}$, then firm h's distance distribution to upstream FDI firms in Eq. (3) can be written as

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

where $dist_{ht}$ is the weighted mean for the distance distribution between firm h and upstream FDI firms indexed by f. When we calculate $dist_{ht}$, the bilateral distances T_{fh}'s are further weighted

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

by the relative importance of upstream FDI firms in industry j in providing intermediate inputs to firm h in industry i (α_{ji}) besides the equal weight of all upstream firms in industry j ($1/n_{jt}$). Since firms in most data do not provide detailed intermediate input suppliers information and therefore firm-level input-output matrix is very rare, we believe these two-tier weights could provide a good approximation for the relative importance of upstream FDI firms in providing intermediate inputs.

The benchmark estimation Substituting (4), (5) and (6) into Eq. (3) and adding control variables and firm-level identically and independently distributed (i.i.d.) shocks, we obtain the benchmark estimation equation:

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

where $\mathbf{x}_{ht}$ is the vector of control variables, δ_t is the time fixed effect, δ_h is the firm-level fixed effect for the time-invariant firm-level heterogeneity, and ϵ_{ht} is the error term that includes firm-level i.i.d. shocks.

The estimates for β_1 and β_2 are the coefficients for the forward spillover channel and its interaction with the firm's distance distribution to upstream FDI firms. The coefficient for the variable $forward_{it}$, 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 better 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 the overall importance of FDI in upstream industries, 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.

Linking with Javorcik (2004) Javorcik (2004) introduces the forward productivity spillover channel through which domestic firms may become more productive if they use inputs from upstream multinationals, and/or if they benefit from complementary service associated with the purchase of FDI inputs. Javorcik (2004) empirically tries to identify the existence of the forward productivity spillover channel by exploring how changes in the relative importance of FDI in upstream industries affect domestic firms' productivity. However, it does not consider the proximity effect through the forward productivity spillover channel. Our paper examines the proximity effect that arises due to the heterogeneous geographical distances between domestic and upstream FDI firms. Here we formalize the link between two papers by showing that our benchmark regression can degenerate to the reduced-form regression (the forward productivity spillover channel only) in javorcik (2004) if we assume that all geographical distances between domestic and upstream FDI firms are identical.

Specifically, if $T_{fh} = T$, the firm-specific effect of distance distribution becomes a constant over time and across firms:[13]

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

Then the benchmark estimation equation degenerates to

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

[13] We have assumed that $\sum_j \alpha_{ji} = 1$ at the beginning of this subsection due to the feature of the input-output matrix.

3 Data

Our dataset covers all manufacturing firms in China with sales greater than 5 million Chinese Yuan[14] 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 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 and/or employment, reducing the sample to 929,365 firm-year observations (with 614,564 Chinese domestic firm-year observations) in 30 manufacturing industries (2 digit industry code: 13-37, 39-43). 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 because multinational firms tend to be large in size.

As documented in Lu et al. (2015), since 1978, China started the open trade policy and allowed inward FDI but the volume and industries of FDI were strictly limited. In 1995, the Chinese central government 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 and encouraged FDI to enter industries that were previously restricted or prohibited. FDI has grown fast afterward. Our data cover exactly the time period with the burst of inward FDI.

In this paper, foreign subsidiaries are defined as firms whose share of subscribed capital from foreign countries, Hong Kong, Macau, and Taiwan is at least 10 percent. Foreign direct 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

[14] Approximately 600,000 dollars at the exchange rate in 2005.

a firm augments from 24.9% in 2000 to 37.5% in 2007. Among 30 manufacturing industries, communication equipment and computers (code 40), transport equipment (code 37), and chemical products (code 26) rank top three of FDI targeting industries and absorb 36.6% of total FDI in 2007. Culture, education and sport activity products (code 24), communication equipment and computers (code 40), and apparel(code 17) 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-level productivity and FDI in upstream industries according to the benchmark regression Eq. (7), we need to construct the measures for some key variables that are not directly available in out data. Below we describe in detail how to construct firm-level productivity, upstream FDI intermediate input share, and distance statistics.

Total factor productivity Traditional productivity measures such as Solow residuals assume a firm's technology parameter as a constant and exogenous to its input factor choice. A firm may, however, make decisions on labor and other inputs based on its technology. Ackerberg, Caves and Frazer (2015), following Olley and Parkes (1996) and Levinsohn and Petrin (2003), assume that a firm's choice of intermediate input reflects its technology changes and then identify technology shocks by employing intermediate input.[15] We employ the Ackerberg, Caves and Frazer (2015) method to estimate firm-level productivity.[16]

[15]Olley and Parkes (1996) assumes that technology shocks can be identified from the use of investment. Due to frequent zeros in investment at the firm level in developing countries, Levinsohn and Petrin (2003) suggests to estimate technology shocks by using intermediate input, the choice of which also reflects productivity shocks. Ackerberg, Caves an Frazer (2006) adopts the use of intermediate input and furthermore solve the collinearity problem in both Olley and Parkes (1996) and Levinsohn and Petrin (2003).

[16]Specifically, we assume a_{hit} evolves according to a first-order Markov process. The technology parameter a_{hit} affects firm h to determine its real intermediate expenditure; so the real expenditure contains information of a_{hit} 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 a_{hit} in the Markov process. Then two moment conditions arise: the innovation of a_{hit} 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.

Upstream FDI intermediate input share We use the weighted average upstream FDI intermediate input share defined according to Eq. (5) as the proxy variable for the amount of intermediate inputs that an individual firm purchased from its upstream foreign subsidiaries. One limitation in our data is that we do not have the detailed information on the composition (from domestic suppliers versus from upstream foreign subsidiaries) of intermediate inputs that a firm procures; in other words, we do not have any firm-level input-output matrix. So we have to use a proxy variable for our analyses. However, this industry-time level proxy variable assumes that an individual firm would purchase its intermediate inputs from all upstream foreign suppliers, which mitigates the potential endogeneity problem between firm-level productivity and its FDI intermediate inputs choice. First, we calculate the foreign capital share for each individual firm. Second, we generate the 2-digit industry aggregate FDI domestic sales share using each firm's foreign capital share as the weights. Third, we apply the 2007 input-output table from *China Statistical Yearbook 2007* to get the upstream FDI intermediate input share.

Firm-level accessibility to upstream FDI firms In our regressions, we use the average distance of a Chinese domestic firm from its foreign intermediate inputs suppliers defined in Eq. (6) as the variable to measure this Chinese domestic firm's accessibility to the FDI intermediate inputs. One unique feature of our data is that firm-level location (at district/country level) is documented, which makes it possible for us to calculate the distance between any two locations. We compute the mean distance between a domestic firm and its upstream FDI firms in each industry, and calculate the weighted average distance for all upstream industries.

Administrative areas in China are divided into three tiers – provinces (also municipalities and autonomous regions), cities, and districts/counties. 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/county.[17] The Annual Surveys of Industrial Production provides firms' location at the

[17]National Bureau of Statistics of China provides a complete list of district codes. The district code is different from

district level. Employing the geographical online applications[18], we collect the information on longitude and latitude for each district code. We then calculate the great circle distance between two locations[19]. 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.[20]

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 of this Chinese domestic firm h's upstream industries. Finally we calculate the weighted average of the mean distances between firm h and FDI firms in each upstream industry by using the Chinese 2007 input-output matrix.

3.2 Summary statistics

We present the summary statistics in table 1. In panel A, the number of domestic firms has grown by approximate 36$\%$ from 68,825 in 2000 to 93,760 in 2007. The mean of the estimated 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, defined as the contribution of net domestic sales by upstream foreign subsidiaries, 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

postal code, as one location uniquely matches one district code but may correspond to multiple postal codes.

[18]maps.google.com.

[19]We apply the Haversine formula to calculate the great circle distance.

[20]It is quite common to use the exogenous great circle distance to represent the trade cost in the literature.

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 approximately 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 will take the log of the distance statistics for all the empirical analyses in the later sections. 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 affects the accessibility of FDI intermediate inputs, and thus affects the forward productivity spillover for Chinese domestic firms.

4 Results

4.1 Benchmark results

We use the fixed-effects panel regressions to estimate the benchmark model Eq. (7) because fixed-effects panel regressions help to remove any unobserved time-invariant heterogeneity that may potentially affect firm-level productivity. We report the estimations results in table 2, in which Panel A reports the results using the log of nationwide distance statistics, while the regressions presented by Panel B use the log of within-province distance measures.

In Panel A (table 2), column 1 presents the benchmark regression (7) with the upstream industry concentration proxy $HHIF$ as the control variable, reported as ”Forward HHI”. The existence of foreign subsidiaries may increase the toughness of upstream industry competition and consequently improve the overall efficiency in the upstream industry. As pointed out by Javocik (2004), even though the benefit from a decrease in upstream industry concentration due to the entry of FDI firms can be viewed as part of the generalized spillover effect, we still try to control for those effects 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_j) as the sum of the squared market shares of the n largest firms in an upstream industry j, where we choose $n = 50$ given the size of manufacturing industries in China. The degree of concentration of upstream industries for any firm in industry i is $HHIF_i = \sum_j \alpha_{ji} HHI_j$, where α_{ji}'s are Chinese 2007 input-output upstream inputs usage rates at 2-digit industry level.

Besides the time-varying industry factor $HHIF$, one may concern that the productivity of Chinese domestic firms is also influenced by some time-varying local factors such as regional demand and supply shocks, developments in infrastructure, improvements in scientific research, and/or trade openness. Following Sun et al. (2002) and Chen and Moore (2010), in column 2, we add real GDP for market supply, real GDP per capital 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 R&D, and ratios of import and export over GDP for openness; all of these control variables are at the province-time level.[21]

The coefficients on $Forward$ and its interaction with the firm's 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 stronger if a domestic firm is geographically closer 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

[21] Data resource: Statistic Yearbook of China.

this firm will increase by 2.8%. In addition, if this firm is 1% geographically closer to its upstream FDI firms (on average 3 kilometers) at the national level,[22] its productivity is on average 0.06% higher than an otherwise identical firm, which is the proximity effect.[23]

We further investigate if a domestic firm's access to upstream FDI firms has heterogeneous impacts on its productivity because of the unbalanced developments of regional economies in China during the time span. The east region has embraced better openness to the world and experienced faster growth; central and west regions, due to their geographic disadvantages and historic conservativeness, have grown much slower compared to the east area. Because of the differentiated developments across regions in China, knowledge transfers through intermediate inputs may also be different across regions, as domestic firms may have different capacities to absorb advanced technologies. We categorize firm locations into the east, central, and west regions.[24] This regional decomposition of China refers to the economic regions. Columns 3-5 in Panel A of table 2 present the estimations for the productivity spillovers for these three different economic regions sub-samples. 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 at the east economic region.

In Panel B of table (2), we employ a different measure of distance statistics — the mean distance between the domestic firm and upstream FDI firms within the same province. We postulate that market frictions may limit 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.

[22] 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 2 standard deviations.

[23] 0.06%=-0.005*12*(-1%), where the average value of $Forward$ is approximately 12 percentage points in the sample.

[24] 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.

Panel B displays the estimation results for whether adding additional control variables (columns 1 and 2) and robustness checks in sub-samples 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) proximity to upstream FDI firms (proximity effect).

4.2 Labor market and capital-good market externalities

Ellison et al. (2010) documents that industries may co-agglomerate because of people. If domestic firms are geographically more proximate to FDI firms, those firms are more likely to hire better trained and more skilled workers who have worked for foreign subsidiaries; as a result, those firms may receive more technology 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 large number of firms provide similar positions, so that they are 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; that is, upstream FDI firms may generate productivity spillovers to domestic firms through the channel of local labor market externality. In order to prove that the benchmark regression results for the general productivity-enhancing effect and the proximity effect are truly the results through FDI intermediate inputs, we need to control for this labor market externality.

Following Alfaro and Chen (2014), for each city, we calculate the likelihood that workers can find new jobs. We first use 1% mini-census survey dataset in 2005[25] that contains numbers of employees in detailed occupations for each industry. After transforming the employment counts of occupations to percentages for each industry, we write out the occupation percentage vector for every industry. Second, we find out the employment similarity for each industry pair by computing

[25]Data resource: National Bureau of Statistics.

the correlation of the occupation vectors for these two industries. We then combine all the bilateral employment similarities into an employment similarity matrix for any arbitrary industry pair. Third, the likelihood of a worker being re-employed in a given city is determined by the employment similarity between his/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 portions of the industries in this city. Intuitively, if a worker in an industry needs to search a new job, the employment similarity between the original and new industries serves as a proxy for the probability that this worker is able to find a position in a new industry, given that the worker enters and searches in that new industry. The city-level output portion of each industry represents the likelihood that any worker will enter that industry. Summing up the probabilities for all industries in the city, we can measure the labor market externality at the city-time level.

Still, we would like to point out that the measure of labor market externality is also time varying. The portions of industry outputs in a given city are changing over time, even though the employment similarities between industries we use in our analyses are industry-level characteristics and therefore time invariant. The time-varying measure of labor market externality reflects the dynamic employment conditions for workers.

Ellison et al. (2010) also documents that industries may co-agglomerate because of goods. Alfaro and Chen (2104) further points out that firms in different industries may be connected not only through intermediate inputs, but also through capital goods. Co-agglomerating firms can obtain better supports for their capital goods because of the scale economies, and reduce their risks in investment because of re-sale opportunities. If domestic firms co-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 stronger productivity spillovers associated with smaller distance statistics are actually caused by the channel of capital good market externality, instead of the channel of intermediate inputs, 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 and/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 Statistics of China does not provide such information. Assuming that usage of different types of capital goods is such an intrinsic industry characteristic that is reserved across countries, we employ the US capital flow table as in Alfaro and Chen (2014). 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/re-sold 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. Columns 1 and 2 display the robustness checks after controlling for the labor market externality at the city-time level, employing nationwide and within-the-province distance statistics respectively. The estimation results in columns 1 and 2 are both qualitatively and quantitatively consistent with the benchmark results. Similarly, we show that benchmark results are still significant after controlling for the capital-good market externality in columns 3 and 4, and for both externalities in columns 5 and 6. The coefficients of labor market externality and capital-good market externality are both positive and significant, which shows that Chinese domestic firms simultaneously benefit from the channels of labor and capital-good markets. Besides these other potential channels, the productivity of any domestic firm is affected through the channel of upstream FDI intermediate inputs.

4.3 Upstream aggregate domestic productivity

We assume homogeneous upstream domestic firms in order to simplify our theoretical model and focus on the productivity spillover effects from upstream FDI firms. Besides the local labor and capital-good markets externalities, another concern about our benchmark empirical setting is that the production efficiency or/and the quality of intermediate inputs of upstream domestic firms are also likely to generate positive productivity spillover effects on downstream domestic firms. And hence, we calculate the upstream aggregate domestic productivity for each 2-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 2-digit industry using firms' real total production as the weights.[26] Then, similar to $Forward$ variable calculation, we apply the input usage shares from the 2007 China's input-output table to generate the upstream aggregate domestic productivity.

Table 4 reports the estimation results that all 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 specification (1) to (3), and from specification (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

[26] We try to use firms' real total sales as the weights as well, and different definitions of the upstream aggregate domestic productivity won't change our regression results at all.

FDI intermediate inputs do not change at all; in addition, the general productivity-enhancing effect from upstream FDI firms is even larger in magnitude.

4.4 Other FDI spillover channels

Besides the forward productivity spillover effect from FDI firms through intermediate inputs which is our main interest in this paper, the FDI spillover literature also document other FDI productivity spillover channels, namely the horizontal and the backward spillover effects.[27]

The FDI horizontal spillover channel refers to the potential productivity effect from the existence of multinational subsidiaries in the same industry of any domestic firm. Multinational firms have a strong incentive to prevent information leakage to their host-country domestic competitors in the same industry; and moreover, the existence of the more productive multinational subsidiaries may discourage domestic firms to improve their productivity. The FDI horizontal productivity spillover effects are very likely to be negative in the data for many host countries. Still we use the share of foreign capital in the same industry of any specific firm to construct variable $Horizontal$ to control for this spillover channel.

The FDI backward spillover channel is believed through the contracts and transactions between downstream multinational subsidiaries and their upstream host-country domestic intermediate inputs suppliers. In this case, foreign subsidiaries are willing to provide some knowledge to their upstream domestic intermediate inputs suppliers in order to guarantee the quality of their production inputs. This backward spillover effects are typically positive in most datasets. So we use the weighted average foreign capital share from all downstream industries for any firm to define variable $Backward$ to control for the FDI backward productivity spillover effect.

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

The definition equations for $Horizontal_{it}$ and $Backward_{it}$ are as following:

$$Horizontal_{it} = \frac{\sum_{f\in i} fshare_{ft} Y_{ft}}{\sum_{f\in i} Y_{ft}},$$
$$Backward_{it} = \sum_{k} \alpha_{ik} \frac{\sum_{f\in k} fshare_{ft} Y_{ft}}{\sum_{f\in k} Y_{ft}},$$

where $fshare_{ft}$ measures the share of foreign ownership for firm f at period t, and Y_{ft} is the real total sales of firm f. The fraction term to be summed in $Backward_{it}$ uses China's 2007 input-output matrix input contribution shares α_{ik} as the weight. Both control variables are varying at the 2-digit industry and time level.

All regression specifications in table 5 control for both FDI horizontal and backward spillover channels. Specifications (1) – (3) use the nationwide distance statistics, and (4) – (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 effects are generally positive.

Adding different combinations of the control variables to our benchmark regression shown by table 2, there is no change for the statistical significance for the general productivity-enhancing effect or the proximity effect through FDI intermediate inputs; and there is very minor change for the economics significance for both effects. Domestic downstream firms do benefit from the existence of FDI intermediate inputs and the effects of these better intermediate inputs decay with the distance statistics.

4.5 The endogeneity of location choice by FDI firms

According to Cheng and Kwan (2000), Amiti and Javorcik (2008) and Chen and Moore (2010), a multinational firm chooses the optimal locations to establish its foreign affiliates. Foreign affiliates are very likely to cluster in some specific locations, and therefore the distance statistics from FDI firms are smaller for the Chinese firms located in those locations. The determinants of location choice, for example, a large local market size and/or good infrastructures, can also be the reasons for domestic firms having high productivity. Specifically, a large market size may cause tougher competition and thus firms need to employ better technology; good infrastructures may facilitate the learning of technology. Consequently, our general productivity-enhancing effect and proximity effect estimations may be biased as a reflection of firm location determinants.

The fixed effects panel regression controls for the time-invariant factors that may affect the location choice by multinational firms. However, it cannot separate any time-varying determinants of FDI location choice from the regression residuals. We conduct a two-step estimation to correct the potential endogeneity problem that is raised from FDI location choice. We first estimate the likelihood of each location in which multinational firms may build up their affiliates. 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, we use an indicator variable whether a location has any FDI firms as the dependent variable, construct both time-invariant and time-varying FDI location determining variables, and estimate the likelihood for each location in which multinational parent firms may choose to set up their affiliates. The dependent variable is a dummy variable that equals one if there is at least one FDI firm in that location (at 6-digit district code level) and zero otherwise. According to Cheng and Kwan (2000), the preferential policies in favor of FDI affect FDI location choice. Therefore, we use a set of dummy variables of different types of economic zones at the district level as the proxies for the preferential policies since 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%.[28] Following Chen and Moore (2010), we also add additional

[28] 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).

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.[29]

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.[30] The random effects probit model is

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

where P_{rt} is a dummy variable that equals one if there is at least one FDI firm at a 6-digit code district r in year t; Φ is the cumulative normal distribution; a is the constant; X_{pt}, the vector of control variables at the provincial level, includes the log of the market potential and the log of the unit labor cost; X_{rt}, the vector of control variables at the 6-digit district level, includes dummies of different economic zones (economic and technology development zone, special economic zone, and border economic cooperation zone); 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 6-digit district r.

Table 6 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

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

[30] 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).

is positively correlated with the market potential and the potential preferential policies from economic and technology development zone[31], 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 first and second specifications employ the nationwide distance statistics, and the third and fourth specifications employ the within province distance statistics, with other control variables only entering the second and fourth specifications.The coefficients for the predicted FDI location probability in all four specifications are significantly positive. That is, if Chinese domestic firms locate at the locations preferred by FDI firms, they will have higher productivity. More importantly, the general productivity-enhancing effect and the proximity effect in all four specifications are qualitatively and quantitatively unchanged from our benchmark estimations shown by table 2 after we control for the endogeneity problem from the FDI location choice.

5 Conclusion

How do upstream FDI firms generate productivity spillovers to host-country domestic firms? Are those spillovers heterogenous across domestic firms?

This paper provides the supporting evidence that positive productivity spillovers transmit through the intermediate inputs from upstream FDI firms. 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. A domestic firm gains more in its productivity if it could get access to more FDI intermediate inputs, and/or if it is closer to upstream FDI firms.

These findings further suggest that if policy makers want domestic firms to absorb productivity

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

spillovers from FDI firms better, they need to design more appropriate stimulating policies according to domestic firms' differentiated access of FDI intermediate inputs. Policies need to target on reducing FDI intermediate input procurement costs for domestic firms due to the proximity effect, and/or on encouraging FDI firms to provide domestic firms with more intermediate inputs that embody advanced technology (the general productivity-enhancing effect).

Table 1: Summary Statistics

Panel A: Productivity and spillover variables

Year	Number of local firm-year observations	ln(TFP) Mean	ln(TFP) Standard deviation	Forward (%) Mean	Forward (%) 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 firm-year observations	Nationwide (km) Mean	Nationwide (km) Standard deviation	Within-province (km) Mean	Within-province (km) 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 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 summary statistics of distances between the firm and all FDI firms in China (nationwide), or between the firm and FDI firms in the same province (within a province).

Table 2: Benchmark Results

Panel A Fixed effects panel regressions: Nationwide

Dependent variable: ln(TFP)	All	All	East	Central	West
Forward	0.011**	0.028***	0.032***	−0.004	0.037*
	(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	0.284	0.259	0.347	0.313
$N.of firms$	239,993	239,993	157,979	56,468	25,551
N	614,564	614,564	395,801	144,547	74,216

Panel B Fixed effects panel regressions: Within-province

Dependent variable: ln(TFP)	All	All	East	Central	West
Forward	0.003***	0.003***	0.003***	0.005***	0.002
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)
ln(Distance statistic) * Forward	−0.199***	−0.061***	−0.091***	−0.060	0.233**
	(0.017)	(0.019)	(0.023)	(0.046)	(0.099)
Forward HHI	−0.0005***	−0.0004***	−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	0.281	0.258	0.347	0.312
$N.of firms$	239,993	239,993	157,979	56,468	25,551
N	614,564	614,564	395,801	144,547	74,216

Note: Distance statistic refers to a firm's mean distance to its upstream FDI firms. Forward HHI is the Herfindahl-Hirschman index for upstream industries. Other control variables include real GDP, real GDP per capital and retail sale, railroad per km^2 and road per km^2, the number of R&D scientists per thousand persons, and ratios of import and export over GDP. East areas include Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, Guangxi, and Hainan; central areas include Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, and Hunan; west areas include Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Ganxu, Shaanxi, Qinghai, Ningxia, and Xinjiang. All other variables are defined in Table 1 and 2. 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

Dependent variable: ln(TFP)	Labor Nationwide	Labor Within province	Capital-good Nationwide	Capital-good Within province	Both Nationwide	Both Within province
Forward	0.031^{***}	0.003^{***}	0.030^{**}	0.003^{***}	0.031^{***}	0.003^{***}
	(0.005)	(0.001)	(0.005)	(0.001)	(0.005)	(0.001)
ln(Distance statistic) * Forward	-0.005^{***}	-0.063^{***}	-0.005^{***}	-0.065^{***}	-0.005^{***}	-0.065^{***}
	(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	0.194^{***}	0.188^{***}			0.149^{***}	0.144^{***}
	(0.020)	(0.020)			(0.023)	(0.023)
Capital-good market externality			0.263^{***}	0.258^{***}	0.153^{***}	0.151^{***}
			(0.032)	(0.032)	(0.036)	(0.036)
Other control v.	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.285	0.282	0.285	0.282	0.285	0.282
$N.of firms$	239,993	239,993	239,993	239,993	239,993	239,993
N	614,564	614,564	614,564	614,564	614,564	614,564

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 Table 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***	0.049***	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***	−0.060***	−0.063***
	(0.001)	(0.001)	(0.001)	(0.017)	(0.019)	(0.019)
Forward HHI	−0.0007***	−0.0008***	−0.0006***	−0.0007***	−0.0006***	−0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Upstream AGGR domestic productivity	0.221***	0.315***	0.287***	0.205***	0.278***	0.249***
	(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	0.284	0.285	0.290	0.281	0.282
$N.of firms$	239,993	239,993	239,993	239,993	239,993	239,993
N	614,564	614,564	614,564	614,564	614,564	614,564

Note: Upstream AGGR (aggregate) domestic productivity is the weighted average productivity of all domestic firms from the upstream industries for the 2-digit industry that the firm belongs to. All other variables are defined in Table 1 and 2. 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	0.031***	0.034***	0.047***	0.004***	0.003***	0.006***
	(0.006)	(0.006)	(0.006)	(0.001)	(0.001)	(0.001)
ln(Distance statistic) * Forward	−0.005***	−0.006***	−0.007***	−0.062***	−0.066***	−0.069***
	(0.001)	(0.001)	(0.001)	(0.019)	(0.019)	(0.019)
Forward HHI	−0.0005***	−0.0004***	−0.0007***	−0.0005***	−0.0003***	−0.0005***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Horizontal	−0.0011	−0.0012*	0.0015**	−0.0003	−0.0004	0.0024***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Backward	0.0002*	0.0002	0.0002	0.0002*	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Other control v.	Yes	Yes	Yes	Yes	Yes	Yes
L and K markets externality controls	No	Yes	Yes	No	Yes	Yes
Upstream AGGR domestic productivity	No	No	Yes	No	No	Yes
R^2	0.284	0.285	0.285	0.281	0.282	0.282
$N.of firms$	239,993	239,993	239,993	239,993	239,993	239,993
N	614,564	614,564	614,564	614,564	614,564	614,564

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

Table 6: 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	0.030***	0.037***	0.003***	0.003***
	(0.154)		(0.005)	(0.005)	(0.001)	(0.001)
ln(Labor cost)	−0.362**	ln(Distance statistic)	−0.005***	−0.006***	−0.167***	−0.046**
	(0.168)	* Forward	(0.001)	(0.001)	(0.018)	(0.019)
Economic and tech.	4.956***	Forward HHI	−0.0006***	−0.0006***	−0.0005***	−0.0004***
development zone	(0.869)		(0.0001)	(0.0001)	(0.0001)	(0.0001)
		FDI locating probability	0.461***	0.368***	0.394***	0.335***
			(0.028)	(0.031)	(0.028)	(0.031)
		Other control v.	No	Yes	No	Yes
$Psudo\ R^2$	0.068	R^2	0.303	0.296	0.298	0.294
$N.of districts$	3,209	$N.of firms$	239,993	239,993	239,993	239,993
N	21,447	N	614,564	614,564	614,564	614,564

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 Table 1 and 2. Standard errors are presented in parentheses. ***, **, and * denote significance at 1%, 5%, and 10% respectively.

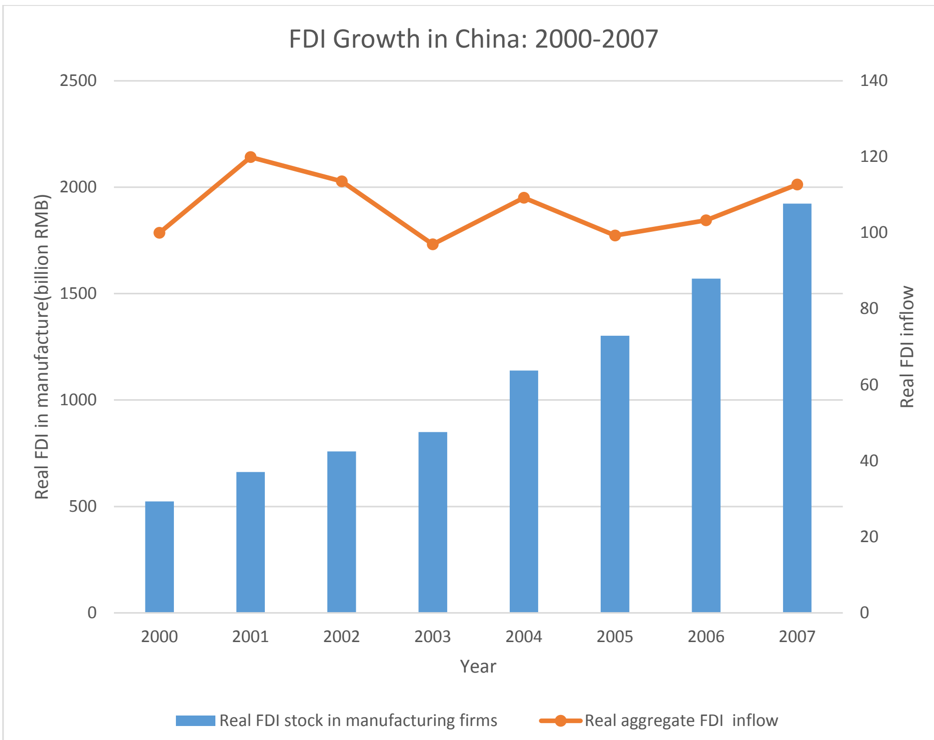

Fig. 1: FDI Growth in China

Note: FDI stock in 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. Aggregate FDI inflow index is calculated from China Statistical Yearbook and FDI inflow in 2000 is normalized as 100. Both variables are deflated by Production Price Index (base year: 1999).

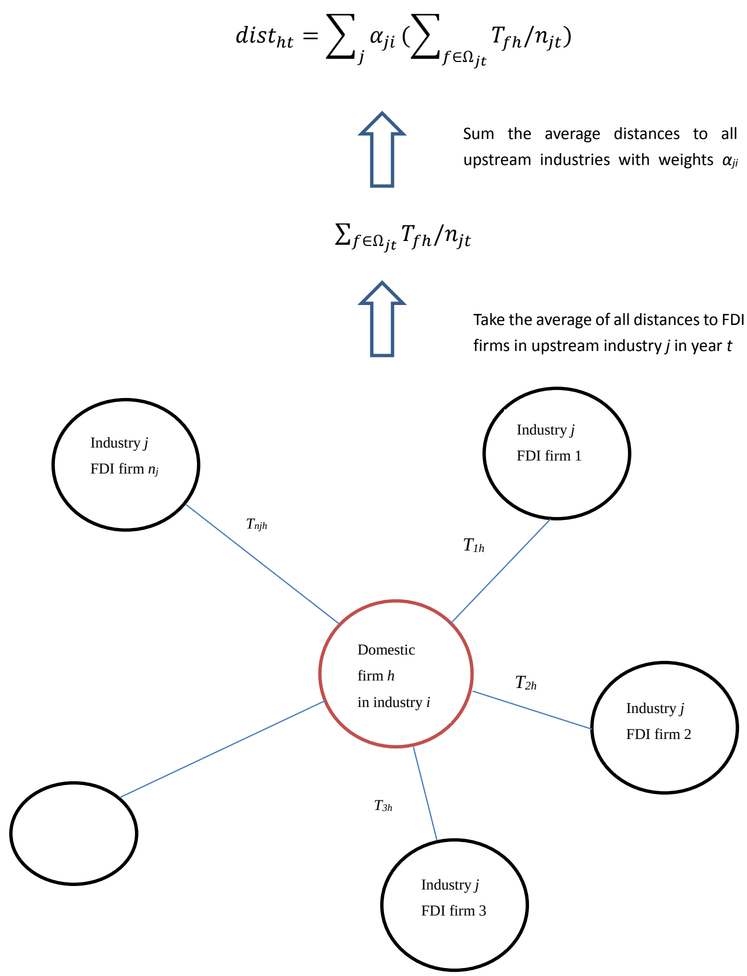

Fig. 2: A Firm’s Distance Distribution

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