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FDI Technology Spillovers, Geography, and Spatial Diffusion

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Abstract: This paper investigates the geographic extent of FDI technology spillovers and associated spatial diffusion. By adopting a spatiotemporal autoregressive panel model as the platform of our study, the complex impact resulting from FDI penetration is separated into spatial direct and indirect effects while accounting for feedback loops among regions. A set of spatially partitioned summary measures is produced to identify and to quantify FDI spillovers from different channels with distinct geographic scopes. Empirical results based on data from China document that the direct impacts of FDI presence to a specific location itself are likely to be negative. Domestic firms mainly benefit from FDI presence in their neighboring regions through knowledge spillovers that have wider geographic scope. Negative market stealing effect nevertheless has no spatial boundary. Policy implications of these findings are discussed.

Key Words: FDI spillovers, spatial diffusion, geography, spatial dynamic panel, Chinese economy.

JEL Classification: R12, F21, O33.

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1. Introduction

Firms tend to agglomerate in specific areas so as to reduce transaction cost and exploit external economies. Such external economies are commonly known as Marshallian externalities of which the central idea highlights that the concentration of production in a particular location generates external benefits for firms in that location through knowledge spillovers, labor pooling, and close proximity of specialized suppliers (Marshall, 1920).[1] The foreign direct investment (FDI) location literature has documented similar self-perpetuating growth or agglomeration pattern of multinational corporations (MNCs) in space and over time (see, among others, Head et al., 1995; Cheng and Kwan, 2000a, 2000b; Blonigen et al., 2005; Lin and Kwan, 2011). The externalities arising from FDI penetration also have long received great attentions from both economists and policy makers. Although the previous literature has provided some evidence of FDI spillovers at both firm and industry levels (Lin et al., 2009; Abraham et al., 2010; Hale and Long, 2011; Xu and Sheng, 2012; Damijan et al., 2013; Merlevede et al., 2014; among other earlier contributions), little is known about the extent to which the regional presence of FDI affects the aggregate productivity of local private firms in spatial dimension. This paper studies FDI spatial spillovers using county-level data supplemented with precise GPS information of China. More specifically, this paper asks: Do domestic private firms benefit from FDI presence in their local and neighbouring regions? How to identify and quantify the geographic extent of FDI spillovers? Do FDI spillovers attenuate with distance? If so, how rapid is the geographic attenuation pattern?

There exists a vast literature on FDI spillovers. FDI presence may benefit domestic firms via channels like labor turnover, demonstration of new technology, competition effect, reverse engineering, and 'learning by watching' (see, among others, MacDougall, 1960; Kokko, 1994; Blalock and Gerlter, 2008). FDI spillovers from MNCs to domestic firms can also be negative. A leading example in the literature is 'market stealing effect' (Aitken and Harrison, 1999).[2] While the penetration of MNCs may bestow positive externalities on domestic firms, it could also generate, at the same time, a negative demand effect, which drags down the productivity of local firms. Another possible source of negative impact comes from foreign firms poaching local talents from domestic firms to the detriment of domestic firms' productivity (Blalock and Gerlter, 2008). The net impact

[1] Marshall (1920) argues that firms can benefit from two types of external economies: 1) economies arising from 'the use of specialized skill and machinery' which depend on 'the aggregate volume of production in the neighborhood' and 2) economies "connected with the growth of knowledge and the progress of the arts" which tie to the 'aggregate volume of production in the whole civilized world'.

[2] Aitken and Harrison(1999) argues that, in the short run, indigenous firms may be constrained by high fixed cost that prevents them from reducing their total cost; therefore, foreign firms with cost advantages due to better technology can steal market share from domestic firms via price competition. As a result, due to a lack of economies of scale, the shrinking demand will push up the unit cost of domestic firms and decrease their operation efficiency.

from FDI presence on domestic firms hence depends on the magnitude of these two opposite externalities.

Though the theoretical arguments are well established, the empirical literature so far provides mixed evidence of the existence, the sign, and the magnitude of FDI spillovers. This is partially due to the fact that the above mentioned channels are operative at the same time even though their impacts may have different scopes and they reach local firms in different manners. Empirical exercises focusing on simple association between domestic firms' productivity and FDI presence can at best summarize an averaged impact resulting from various channels and dimensions, but it can barely reveal the underlying mechanism of FDI spillovers. Focusing predominantly on this averaged impact will likely dilute the genuine and rich variations of FDI spillovers and result in misleading conclusion. Identification problem thus remains a challenging but vital issue in the FDI spillovers literature.

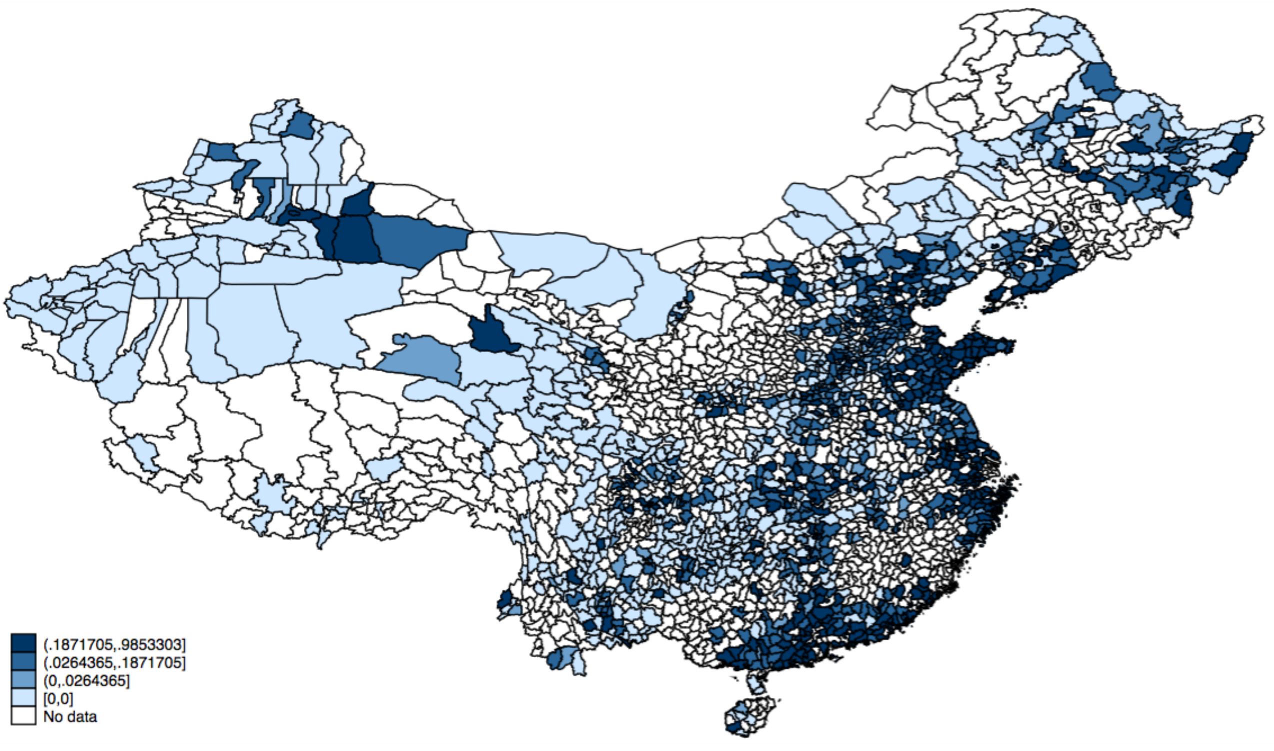
In this paper, we use geography to identify and quantify FDI spillovers. Geographical distance determines the costs and the attenuation pattern of technology diffusion, which may reduce the likelihood for indigenous firms that are distant from MNCs to expropriate spillovers. The fact that spatial interactions are shaped by feedback loops (i.e., from one location to its neighbors, and then neighbors' neighbors, and finally back to the original location indirectly) further complicates the identification issue and the interpretation of resulting estimates. Our method described in section 3 is capable of quantifying separately the direct and indirect impacts, as well as producing a set of partitioning summary measures to describe the rate of decay pattern across space and over time. Further, we exploit the fact that different spillover channels should have different geographic scopes to identify spillovers from different sources. For instance, it is reasonable to expect positive knowledge spillovers should have a wider geographic scope than negative poaching effect, though both are intermediated via the labor turnover channel. In view of the rapid development in modern information technology, the diffusion barrier and communication cost for knowledge spillovers have been significantly reduced. Labor mobility across regions, however, is still subject to high reallocation expenses that increase with distance. It is thus more difficult for MNCs to poach talents from distant domestic firms, implying that poaching effect should decay relatively faster. Consequently, knowledge spillovers can be identified with wider geographic scope, whereas poaching effect can be identified with more local scope. Negative market stealing effect, on the other hand, should have no boundary as its impact could easily spread out to the whole country through integrated markets. Given the increasingly diverse and convenient distribution channels for products, sales network nowadays is hard to be segmented. Market stealing impact hence should appear not just locally but also in wide geographic scope. Our empirical findings confirm the above conjectures. Negative poaching effect in our estimations appears only in local scope while positive knowledge spillovers become dominant in wider geographic scope. Negative market stealing effect, however, is always quantitatively significant regardless of geographic scope.

We employ two proxies to capture FDI spillovers in this paper. Many recent studies emphasize the role of labor market pooling in the process of spatial knowledge spillovers. Fallick et al. (2006) and Freedman (2008) illustrate that industry co-agglomeration facilitates labor mobility (moving among jobs). Ellison et al. (2010) further document that industries employing the same types of workers tend to co-agglomerate. Duranton and Puga (2004) explore the micro-foundations based on spatial externalities arising from sharing, matching and learning among individuals. Kloosterman (2008) and Ibrahim et al. (2009) both argue that industry agglomeration promotes knowledge spillovers since it facilitates individuals to share ideas and tacit knowledge. In line with these studies, we adopt regional employment share of foreign firms as one of the proxies for FDI spatial spillovers to capture spillovers from labor market pooling. To capture the potential pecuniary externalities suggested by Aitken and Harrison (1999) (such as market stealing or crowding out of local firms) we also use regional sales income share of foreign firms as the second proxy.

There are other papers studying the spatial impact of FDI using geographical information. Using aggregate data at the city level, Madariaga and Poncet (2007) show that the economic growth of Chinese cities benefit not only from their own FDI inflows but also from FDI flows to the neighboring cities. Monastiriotis and Jordaan (2010) and Tanaka and Hashiguchi (2015) both document that FDI presence generates significant productivity spillovers at both local and regional levels. This paper contributes to the literature in the following aspects: (a) We provide county-level evidence of FDI spatial spillovers in China, taking into account spillovers through spatial feedback loops, thereby allowing separate identification of intra- and inter-regional spillover effect; (b) In view of the fact that spillover effect gradually spreads over time and across space, we capture the diffusion dynamics by means of a spatiotemporal dynamic panel data model which, to the best of our knowledge, has not been applied before in the FDI spillover literature; (c) We exploit geographical information to disentangle various spillover effects emanating from different sources and quantify their impact and scope of influence.

The regional presence of FDI is largely driven by the related policy in China. With an aim of facilitating local firms to learn from nearby MNCs, five Special Economic Zones (SEZs) were set up in the early 1980s to attract foreign capital by exempting MNCs from taxes and regulations.[3] These five special economic zones are Shenzhen, Xiamen, Hainan, Zhuhai, and Shantou, which are all located in coastal areas. In view of the early success of this experiment, similar schemes, such as Open Coastal Cities (OCCs), Open Coastal Areas, Economic and Technological Development Zones (ETDZs) and Hi-Tech Parks, were set up subsequently to cover broader and inner regions in the later years.[4] Fig. 1 compares the FDI spatial density distribution (measured as fixed asset share of FDI in a specific county) between 1998 and 2007. As shown in the graphs, FDI presence in 1998 mainly clusters in coastal and some central regions of China. The graph for 2007 indicates that the clustering pattern has been getting stronger over time. While the majority of clusters remain in coastal and central regions, FDI presence has been directed and spread to broader and inner areas in China. In view of the fact that similar place-based FDI policy has been widely implemented in the rest of the world, our empirical results also generate important implications on the experiment of policy-driven clustering among indigenous firms and MNEs in developing countries.

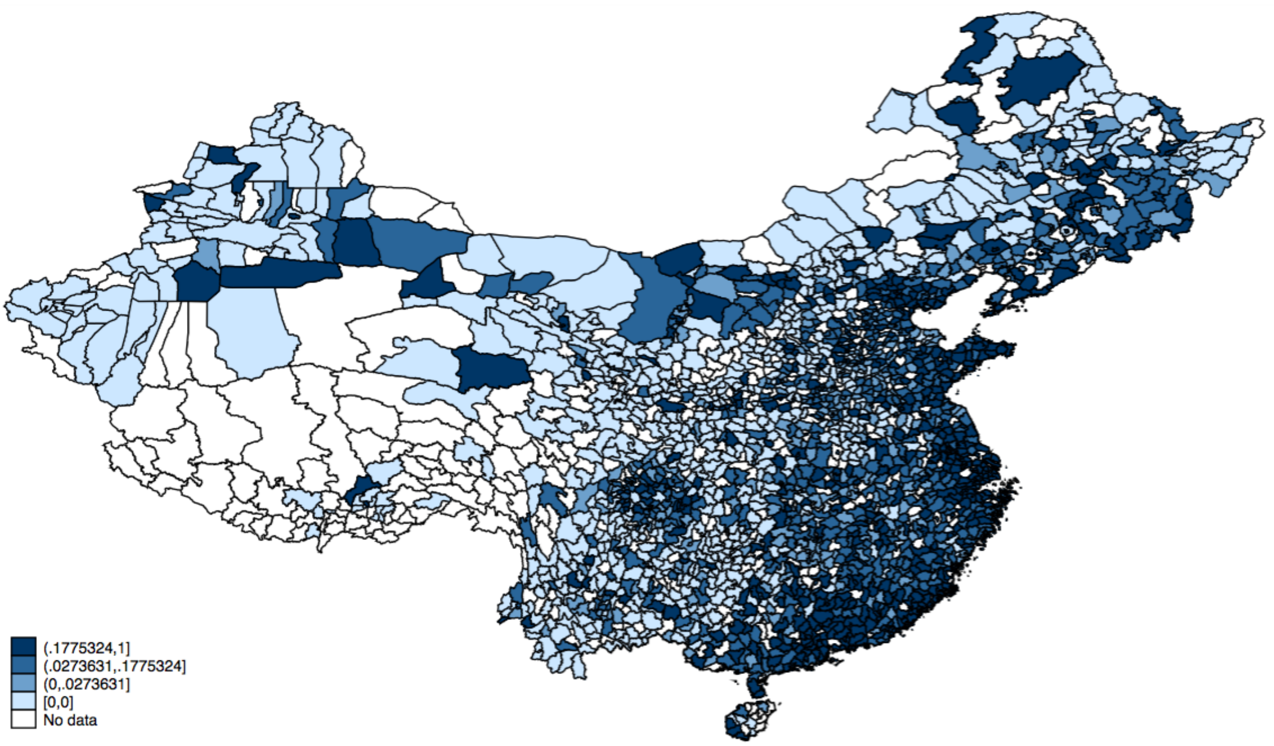
FDI density (fixed asset share) at county level (1998)



[3] Commonly known as the strategy of ‘swapping market access for technology’.

[4] See Cheng (1994) for a detailed review of the evolution of FDI policy in China.

FDI density (fixed asset share) at county level (2007)



Source: Authors' calculation based on NBS-CIE database. FDI density is measured by fixed asset share of FDI in each county, i.e., the value of fixed asset of foreign firms divided by the total fixed asset in a county. The color code on the map indicates the classes of density in quartiles, with the darkest color corresponding to the class of the highest density.

Fig. 1. FDI spatial density distribution at county level.

The rest of this paper is organized as follows. Section 2 describes the data and presents the results of exploratory spatial data analyses. Section 3 presents a spatiotemporal dynamic panel model that incorporates the spatial features observed in section 2. Section 4 discusses various econometric issues and presents empirical results. The final section concludes with a summary and suggestions for future research.

2. Data and Exploratory Data Analysis

2.1. Data

Data employed in this paper come from the annual census of above-size manufacturing firms of China from 1998 to 2007. The National Bureau of Statistics (NBS) of China conducts the census. The database (known as the Chinese Industrial Enterprises Database, NBS-CIE database henceforth) reports census data for Chinese manufacturing firms with annual sales revenue over 5 million RMB. There are several variables (including the Chinese standard location indicator, province code, city code, county code, district code, as well as firms' full address) can help us identify the location of a firm. Of all these variables, province code, city code and county code are most complete and consistent over the years. Information specifying the distance between individual firms is not available. We hence define ‘region’ as a county in this paper. Consequently, all variables in this paper are aggregate county-level data constructed from firm-level information. This results in an unbalanced panel data set with 1357 counties in 1998 and 2023 counties in 2007, respectively. The longitude and latitude information of the counties are obtained from the GADM database of Global Administrative Areas.[5]

Domestic private firms in this paper are defined as firms that have not received equity capital from foreign investors or from any level of China’s government.[6] Appendix A reports the information of firms’ ownership structures and their proportions in each year in the database. More specifically, in this paper, domestic private firms are firms with ownership structures from column (1) to column (7) in the table. FDI firms correspond to columns of ‘Foreign Firms’ and ‘Sino-Foreign Joint Ventures’.

The first step of our data analysis is to estimate total factor productivity (TFP) at firm level and then aggregate them up to the county level. In Appendices B and C, we describe in details our data cleaning process and the procedure of constructing county-level TFP from firm-level data.

2.2. Exploratory Spatial Data Analysis

There are strong theoretical reasons why regional total factor productivities (TFPs) might be spatially correlated. Ciccone and Hall (1996) prove theoretically that the density of economic activity would affect productivity in spatial dimension through externalities and increasing returns. They also provide empirical evidence showing that more than half of the variance of productivity across U.S. states can be attributed to the differences in the spatial density of economic activity. In this section we present empirical evidence that county level TFP of domestic private firms in China also exhibits very strong spatial autocorrelation.

By definition spatial autocorrelation describes the coincidence of value similarity with locational similarity (Anselin, 2001). Positive spatial autocorrelation means high (or low) values of a variable tend to cluster together in space, and negative spatial autocorrelation indicates high (low) values are surrounded by low (high) values. As standard measures, both global and local Moran’s *I* statistics

[5] GADM is a spatial database of the location of the world’s administrative areas (or administrative boundaries). The database describes where these administrative areas are (the spatial features), and for each area it provides some attributes, such as the name, geography area, longitude and latitude, and shape. Source: http://www.diva-gis.org/.

[6] This study does not attempt to address and evaluate the impact of FDI on the productivity of China’s state-owned enterprises. This issue may be investigated in future research.

are commonly adopted in the literature to measure the strength and significance of spatial autocorrelation. Global Moran's *I* statistic is defined as

$$I_t = \frac{n}{S_0} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_{it}-\mu_t)(x_{jt}-\mu_t)}{\sum_{i=1}^{n}(x_{it}-\mu_t)^2} \tag{1}$$

where x_{it} is the variable of interest (TFP) for county *i* at time *t*; μ_t is the mean of variable x in year *t*; w_{ij} is a spatial weight that depicts the relative similarity of two localities (counties i and j) in space. n is the number of counties. S_0 is a scalar factor equal to the sum of all w_{ij}. In this paper, we define the spatial weight as inversed geographical distance between two localities, i.e.,

$$w_{ij} = \begin{cases} (d_{ij})^{-1} & if \quad i \neq j \\ 0 & if \quad i = j \end{cases} \tag{2}$$

where d_{ij} denotes the geographical distance between counties i and j. Similarly, local Moran's *I* statistic is defined as

$$I_{it} = \frac{(x_{it}-\mu_t)\sum_{j=1, j\neq i}^{n} w_{ij}(x_{jt}-\mu_t)}{S_i^2} \quad \text{where} \quad S_i^2 = \frac{\sum_{j=1, j\neq i}^{n}(x_{jt}-\mu_t)^2}{n-1} - \mu_t^2. \tag{3}$$

Local Moran's *I* is an example of Local Indicators of Spatial Association (LISA) defined in Anselin (1995).

By comparing equations (1) and (3), it can be shown that, for a row standardized weights matrix, the global Moran's *I* equals the mean of the local Moran's *I* statistics up to a scaling constant. Consequently, while local Moran's *I* statistics describe the extent of significant spatial clustering of similar values around each particular locality (county i), global Moran's *I* yields one statistic to summarize these local information across the whole study area. For both global and local Moran's *I*, a positive value for *I* statistic indicates that a county has neighboring counties with similarly high or low attribute values (TFP), i.e., this county is part of a cluster. A negative value for *I* statistic indicates that a county has neighboring counties with dissimilar values, i.e., this county is an outlier.

Table 1 reports the global Moran's *I* statistics for aggregate county level TFP for domestic private firms. As shown in the table, Moran's *I* statistics are significant and positive in all cases, indicating positive spatial autocorrelation for TFP. Notice that the magnitude of the statistics increases significantly over time, indicating an escalating pattern of spatial clustering in terms of TFP innovation for domestic private firms during the sample period. This observation motives us to explicitly incorporate both space and time autocorrelations in the econometric model described in section 3.

Table 1

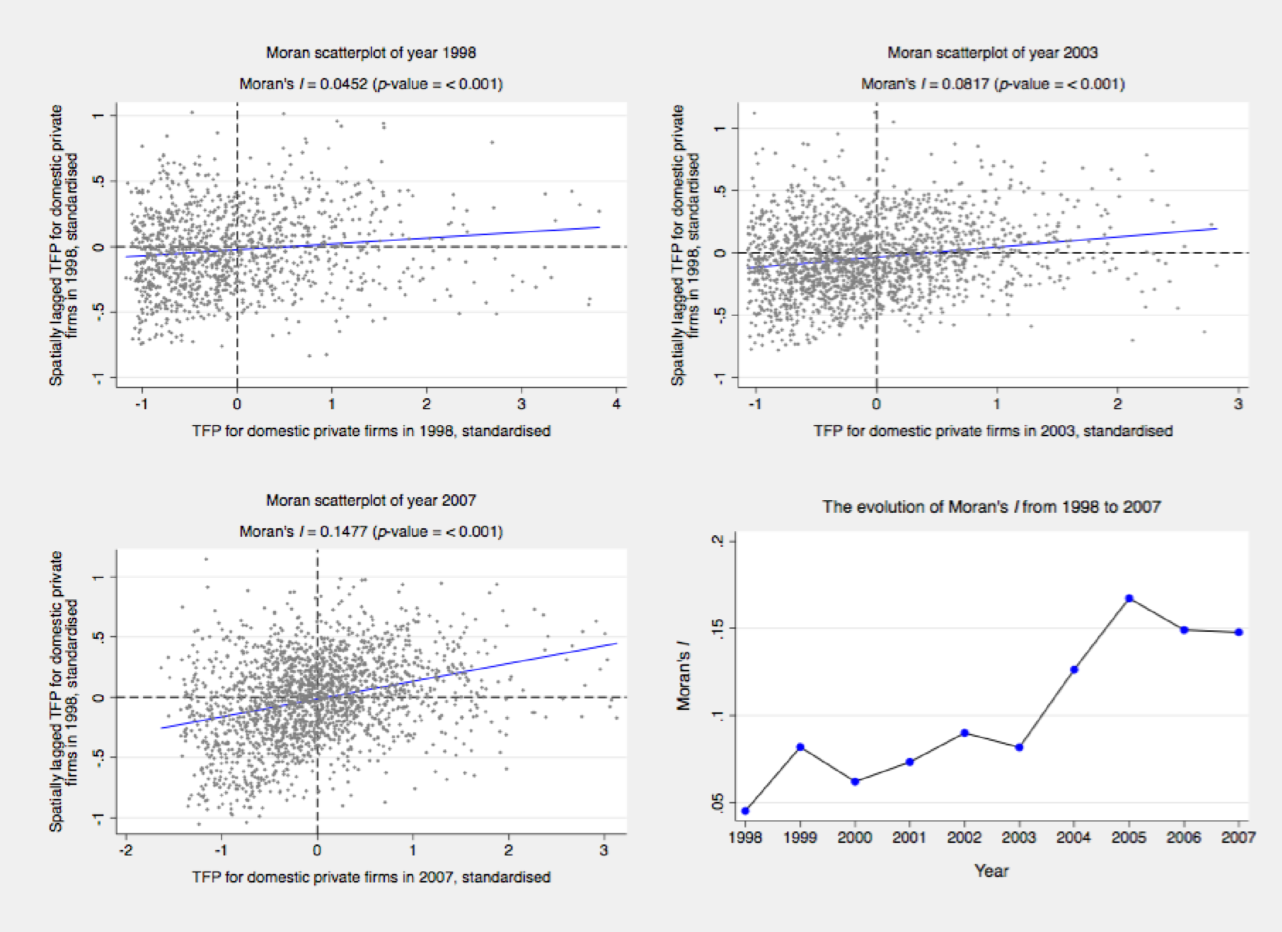
Global Moran's *I* for county-level TFP of domestic private firms.

	Moran's *I*	Standard Deviation	*p*-value
10 nearest neighbors			
TFP in 1998	0.0452	0.0106	< 0.001
TFP in 2003	0.0817	0.0097	< 0.001
TFP in 2007	0.1477	0.0102	< 0.001
5 nearest neighbors			
TFP in 1998	0.0582	0.0141	< 0.001
TFP in 2003	0.0910	0.0120	< 0.001
TFP in 2007	0.1557	0.0122	< 0.001

Note: Authors' calculation based on NBS-CIE database. All statistics are calculated based on row-standardized spatial weights matrix with 5 or 10 nearest neighbors have non-zero spatial weight w_{ij}. County level TFPs are constructed as the weighted average of firm-level TFPs with the weights being the value added shares of each firm in the underlying county. Statistics for other years show the same upward pattern with minor fluctuations. To conserve space, only the statistics for the first, the middle, and the last year are reported.

Equation (1) essentially describes the correlation between spatially weighted (spatial lag) variable, Wz, and z itself, where z is the variable of interest (TFP) that has been standardized. Consequently, Moran's *I* statistic can also be illustrated by plotting Wz against z while the statistic is equivalent to the slope of the linear regression of Wz on z. Fig. 2 presents these Moran scatterplots of county-level TFP for the first, the middle, and the last year of our sample.[7] Since variables are standardized, plots over time are comparable. It is clear that, over time, there is a tendency that more observations are located in the upper-right quadrant, corresponding to high-high values. The evolution of Moran's *I* from 1998 to 2007 also shows that, though with some small fluctuations, the statistics had increased over the years. The data hence reveal clearly that domestic private firms' TFP is becoming more clustered.

[7] In each graph, the four quadrants in the plot group the observations into four types of spatial interaction: namely, high values located next to high values (high-high cluster in upper right-hand corner), low values located next to low values (low-low cluster in lower left-hand corner), high values located next to low values (high-low outlier in lower right-hand corner), and low values located next to high values (low-high outlier in upper left-hand corner).



Note: Authors' calculation based on NBS-CIE database. County level TFPs are constructed as the weighted average of firm-level ln(TFP)s with the weight being the value added share of each firm in the underlying county. All statistics are calculated based on row-standardized spatial weights matrix with 10 nearest neighbors.

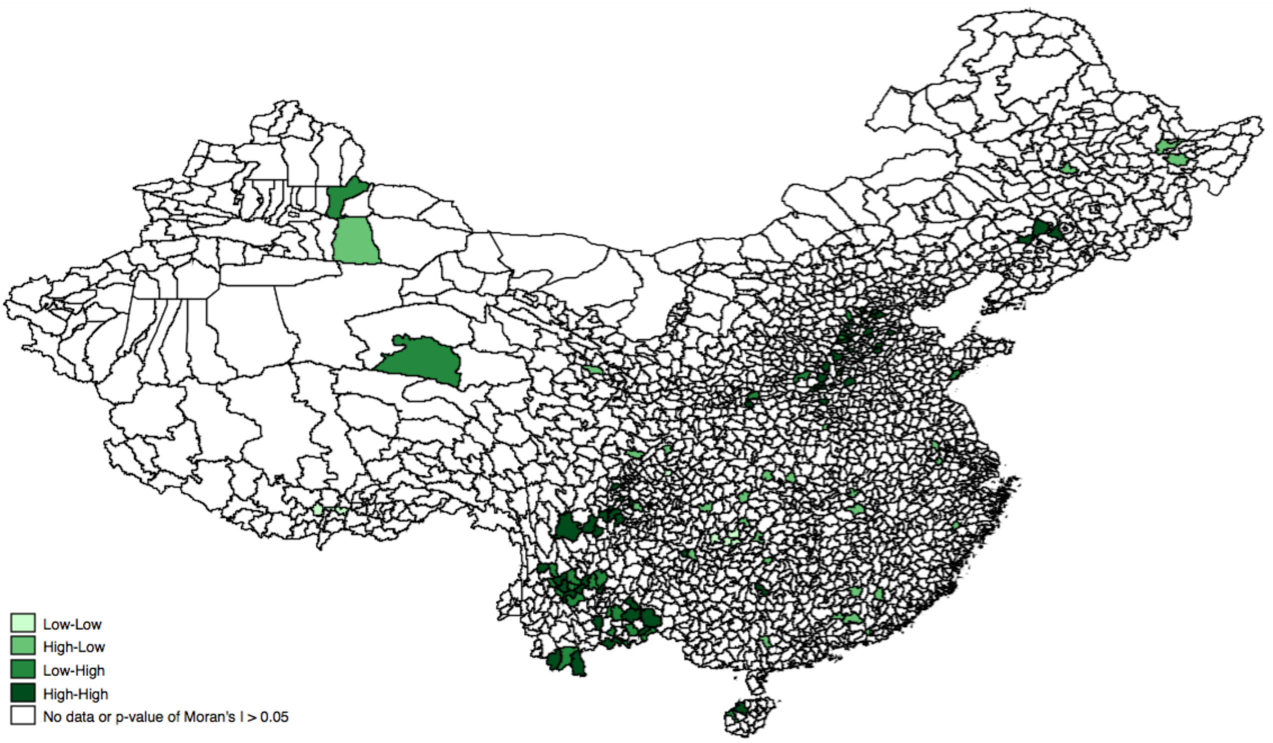
Fig. 2: Global Moran's *I* of county-level TFP.

Fig. 3 presents a comparison of local Moran statistic for TFP of domestic private firms between 1998 and 2007. To highlight the key areas of clustering, only counties with significant (at 5% level) local Moran statistics are plotted. The color code on the map indicates the corresponding quadrant in the Moran scatterplots (Fig. 2) to which the counties belong. The graphs show significant change of clustering location during the sample period. In 1998, there are only several clusters covering limited regions.[8] In 2007, however, high-high clusters spread to almost the entire central and central-northern parts of China and the province of Yunnan, while the high-low outliers and low-low clusters spread to most of the southern coastal regions of China. It is apparent that, for TFP level of domestic private firms, over time, the location of clusters has spread out to broader area and the spatial clustering pattern (both high-high and low-low clusterings) has become more prominent over the decade of the sample. An interesting observation is that, when comparing Fig. 1 and 3, it

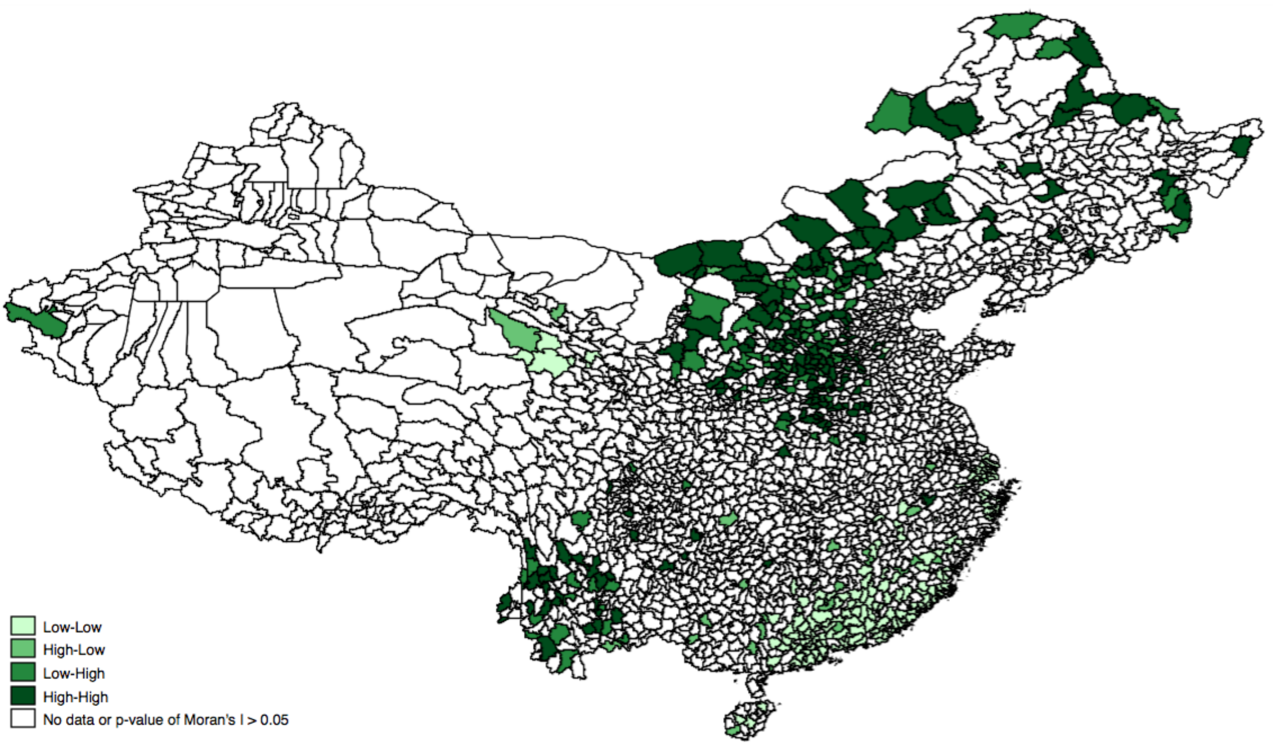
[8] The high-high clusters are mainly in 1) the province of Yunnan; 2) around Beijing and the provinces of Shanxi and Hebei; and 3) some areas in Inner Mongolia. There are also high-low outliers or low-low clusters in 1) provinces of Guangxi and Guangdong and 2) provinces of Heilongjiang and Jilin.

seems that areas with high-high clustering of domestic private firms's TFP are also areas with low FDI density, while areas with low-low clustering are areas with high FDI density.

LISA cluster map of county-level TFP of domestic private firms in 1998



LISA cluster map of county-level TFP of domestic private firms in 2007



Note: Authors' calculation based on NBS-CIE database. LISA = Local Indicator of Spatial Association.

Fig. 3: LISA cluster map of domestic private firms.

To sum up, exploratory spatial data analysis reveals salient spatial autocorrelation feature for county-level TFP of domestic private firms. There is a strong tendency that TFPs are getting more clustered throughout the sample period. In the next section, we further explore these observations in a spatiotemporal model that incorporates both spatial interactions across regions and spatial technology diffusion of FDI.

3. The Empirical Model

To estimate the extent of FDI spillovers and its diffusion pattern over time and across space, we generalize the spatiotemporal partial adjustment model in LeSage and Pace (2009, Chapter 7) to come up with the spatiotemporal dynamic panel regression in (4) as the platform for our empirical analysis, where the spatial weights w_{ij} are inversely proportional to the geographical distance d_{ij} between two regions *i* and *j* as stated in (5)[9]:

$$\begin{aligned} TFP_{it} = {} & \tau TFP_{it-1} + \rho\sum_{j=1}^{N} w_{ij} TFP_{jt-1} + \beta_1 SOE\_presence_{it} + \gamma_1 \sum_{j=1}^{N} w_{ij} SOE\_presence_{jt} \\ & + \beta_2 FDI\_employment_{it} + \gamma_2 \sum_{j=1}^{N} w_{ij} FDI\_employment_{jt} \\ & + \beta_3 FDI\_sales_{it} + \gamma_3 \sum_{j=1}^{N} w_{ij} FDI\_sales_{jt} \\ & + \delta_t + \alpha_i + \varepsilon_{it} \end{aligned} \tag{4}$$

$$i = 1,2,\dots,N; \quad t = 1999-2007.$$

where

$$w_{ij} = \begin{cases} (d_{ij})^{-1} & if \quad i \neq j \\ 0 & if \quad i = j \end{cases} \tag{5}$$

The dependent variable TFP_{it} in (4) is county-level TFP described in Appendix C. We include two explanatory variables as proxies for FDI penetration, namely, the employment share and the sales income share of foreign firms in a county:

$$\begin{aligned} FDI\_employment_{it} &= \frac{Employment_{it}^{FDI}}{Employment_{it}^{T}} \quad \text{and} \\ FDI\_sales_{it} &= \frac{Sales\ Income_{it}^{FDI}}{Sales\ Income_{it}^{T}} \end{aligned} \tag{6}$$

where superscript T refers to all firms (both domestic and foreign) in a county, and superscript *FDI* refers to foreign firms only. The two proxies are expected to identify different channels of FDI

[9] Summary statistics of variables in Eq. (4) are reported in Appendix D.

spillovers. FDI employment share is expected to capture spillover effect that diffuses through the labor market channel (e.g. positive spillovers such as technology transfers, learning-by-watching, and knowledge spillovers via labor turnovers; negative spillovers such as poaching local talents from domestic firms). In contrast, sales income share is expected to capture the pecuniary externalities such as market stealing and crowding out of local firms. In view of the prominence of the state-owned sector in China and its well documented impact on the private sector, we also include the fixed-asset share of state-owned enterprises in a county as a third explanatory variable:

$$\left(SOE\_presence\right)_{it} = \frac{Fixed\ Assets_{it}^{SOE}}{Fixed\ Assets_{it}^{T}} \tag{7}$$

where superscripts T and SOE refer to all firms and state-owned firms respectively.[10] Finally, our panel data structure allows us to include two fixed effects that control for the impact of unmeasured nationwide events and local heterogeneity. Time-specific fixed effect δ_t captures macroeconomic or policy events that have nationwide impact on productivity; and region-specific fixed effect α_i captures unmeasured local characteristics (such as absorptive capacity, human capital, and geography) that exert heterogeneous impact on productivity.[11]

With spatial interactions and temporal adjustments explicitly incorporated by the two autoregressive terms, $\sum_{j=1}^{N} w_{ij} TFP_{jt-1}$ and $\boldsymbol{TFP_{it-1}}$, equation (4) implies that a change in a single observation associated with any explanatory variable, located in region *i* as of time *t*, will generate direct impact on the region itself (i.e. intra-regional impact $\partial TFP_{it+s} / \partial x_{it}$) and potentially indirect impact on other region *j* (i.e. inter-regional impact $\partial TFP_{jt+s} / \partial x_{it}$), starting from time *t* and extending all the way to indefinite future. These multipliers include the effect of spatial feedback loops. For instance, a first order feedback effect means a change of observation x_{it} in region *i* affects TFP_{jt} in region *j* (region *i*'s immediate neighbor), which in turn affects TFP_{it} in region *i* via the spatial autoregressive term. These feedback loops arise because region *i* is considered as a neighbor to its neighbors, so that impacts passing through neighboring regions will create a feedback impact on region *i* itself. The path of these feedback loops can be extended with the order of neighbors getting

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[10] The impact of SOEs on private section is discussed in Huang (1998), Bai et al. (2000), Bai et al. (2004), and Huang et al. (2008). SOEs might generate crowding out effect, as well as creating distortions in both input and output markets (especially in the financial market), which all have significant impact on private firms.

[11] Recent literature (e.g. Damijan et al. 2013) emphasizes the role of firm heterogeneity (e.g. size, absorptive capacity, technology, etc) in explaining the impact of FDI. We therefore expect county heterogeneity will also be important in the current context.

higher. Consequently, by incorporating these two autoregressive terms, our model is capable of accounting for spillovers among domestic firms resulting from Marshallian agglomeration in space.

Often interest centers on the accumulated multiplier matrix $S_k(W)$ whose (i, j) element is the accumulated impact $\sum_{s=t}^{\infty} \partial TFP_{jt+s} / \partial x_{it}$. Averaging over the n regions gives the following summary measures of spatial impacts introduced by LeSage and Pace (2009):

$$Average\ Total\ Direct\ Impact\ (ATDI) = n^{-1} tr S_k(W) \tag{8}$$

$$Average\ Total\ Impact\ (ATI) = n^{-1} \iota' S_k(W) \iota \tag{9}$$

$$Average\ Total\ Indirect\ Impact = ATI - ATDI \tag{10}$$

where tr is the trace operator and ι is a column of ones. By rewriting (4) as a distributed lag model and then differentiate, it can be shown that the spatial accumulated multiplier matrix follows the formula

$$\begin{aligned} S_k(W) &= (I - \rho^* W)^{-1} (\beta_k^* I + \gamma_k^* W) \\ &= \left[I + \rho^* W + \left(\rho^*\right)^2 W^2 + \cdots \right] \left(\beta_k^* I + \gamma_k^* W \right) \\ &= \underbrace{\left[\beta_k^* I + \gamma_k^* W \right]}_{\substack{\text{zero-order} \\ \text{feedback loop}}} + \rho^* \underbrace{\left[\beta_k^* W + \gamma_k^* W^2 \right]}_{\substack{\text{first-order} \\ \text{feedback loop}}} + \left(\rho^*\right)^2 \underbrace{\left[\beta_k^* W^2 + \gamma_k^* W^3 \right]}_{\substack{\text{second-order} \\ \text{feedback loop}}} + \cdots \end{aligned} \tag{11}$$

where

$$\rho^* = \frac{\rho}{1-\tau}, \quad \beta_k^* = \frac{\beta_k}{1-\tau}, \quad \gamma_k^* = \frac{\gamma_k}{1-\tau} \tag{12}$$

It is of interest to examine the spatial diffusion profile of the multiplier effect imbedded in the power series expansion in (11). The profile reveals the extent to which the impact of explanatory variable k spreads from lower-order neighbors to higher-order neighbors across space. The speed of diffusion is parsimoniously parameterized by ρ^* which in turn is determined by the time and spatial autoregressive parameters τ and ρ.

To sum up, by adopting a spatiotemporal framework, our empirical model explicitly accounts for a) spillovers from FDI and among domestic firms, and b) spillovers through spatial feedback loops across space and over time via the spatiotemporal autoregressive terms. The squared bracket terms in the third line of (11) represent spatially partitioned effects, where powers of W in the squared brackets in the second line capture the weights associated with the observations themselves (zero-order impacts with W^0), immediate neighbors (first-order impacts with W^1), neighbors of neighbors (second-order impacts with W^2), and so on. These spatially partitioned summary measures are the results of complex FDI spillovers being disentangled into narrow and wide geographic scopes, which in turn can be used to identify and quantify spillovers from different channels. It is also due to these complications, the focus of this paper will be on how to generate and interpret these spatially partitioned effects base on the estimated model. To be more specific, equation (4) is estimated to obtain consistent parameter estimates as an initial step. We then apply simulation-oriented Bayesian approach to generate posterior distribution of the objects of interest. More details are described in the following section.

4. Estimation Issues and Empirical Results

4.1. Estimation Issues

As the first step of our empirical analysis, system-GMM estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) is employed to consistently estimate the parameters in Equation (4). Recent Monte-Carlo studies document that, in the context of dynamic spatial panel model, system-GMM is the method of choice in terms of bias, root mean squared error, and standard error accuracy (Kukenova and Monteiro, 2009; Jacobs et al. 2009). Jacobs et al. (2009) also demonstrates that the combination of collapsing the instrument matrix and limiting the lag depth of the dynamic instruments substantially reduces the bias in estimating the spatial lag parameter, but hardly affects its root mean squared error. We follow the recommendations of this line of literature in adopting the spatial system-GMM estimator and judiciously choosing the instruments. The setup of moment conditions follows Kelejian and Prucha (1999), i.e., both space-time lagged dependent variable and space lagged independent variables are included in the instrument list on top of the conventional instruments suggested by Blundell and Bond (1998).

4.2. Empirical Results

Table 2 reports system-GMM estimation results of the spatiotemporal autoregressive panel model in (4) and a conventional dynamic panel model without spatial interaction effects. Both time and spatial autocorrelation coefficients are positive and significant, suggesting fairly strong time and spatial self-reinforcing effects of total factor productivity for domestic private firms at county level, suggesting significant spillovers among local firms resulting from Marshallian agglomeration in space and over time. Estimated coefficients for own-regional (intra-regional) FDI presence are in most cases negative and significant, indicating negative immediate impact from FDI to domestic firms located in the same county. Note that, however, these two benchmark regressions should be interpreted differently. For the spatiotemporal model, the partial derivative of TFP with respect to a change in FDI presence not only measures the direct impact (as captured by β_2 and β_3 in (4)) of this change on the own region but also measures its indirect impact (as captured by γ_2 and γ_3 in (4), the result of the feedback loops from the own region to neighboring regions and then back to the own region). Consequently, the difference in the magnitude of coefficients is due to the fact that conventional regression without spatial interactions is unable to capture these feedback effects and thus provides potentially biased estimates.

The presence of SOEs, as captured by β_1 and γ_1, seems to generate negative impacts on domestic firms. This is consistent with the results documented in the literature. SOEs tend to generate crowding out effect as well as distortions in both input and output markets. Note that the inter-regional impact of SOEs presence, as captured by γ_1, is small in magnitude and not significant. This could be due to the fact that SOEs in China tend to focus on local regional markets for well-documented cellular structure and localism; consequently, private firms are less affected by SOEs from neighboring regions.

Table 2
Benchmark regression.

Dependent variable: TFP	No spatial effects	Spatiotemporal model
Time lagged TFP	0.259	0.307
	(0.046)	(0.044)
SOE presence	-3.667	-3.704
	(0.482)	(0.511)
FDI presence: employment share	-1.459	-0.540
	(0.675)	(0.811)
FDI presence: sales income share	-1.468	-2.353
	(0.672)	(0.650)
Space-time lagged TFP		0.305
		(0.152)
Spatially lagged SOE presence		-0.677
		(1.354)
Spatially lagged FDI presence: employment share		21.006
		(12.311)
Spatially lagged FDI presence: sales income share		-32.423
		(12.464)
Hansen Statistic	3.433	11.121
Hansen Statistic P-value	0.842	0.744
D.O.F of Hansen Statistic	7	15
Number of Instruments	20	32
N	14560	14560

Note: Results reported are two-step system-GMM estimates. Standard errors in parentheses. Windmeijer's (2005) correction method for the two-step standard errors is employed. Year dummies are included in all regressions. Collapsed instrument matrix technique is employed to reduce the instrument count.

In what follows we describe how spatial direct and indirect impacts, as well as a set of partitioning summary measures, can be generated from the estimated spatiotemporal model and how they can be used to describe the extent of FDI spillovers across space and over time. To account for spatial feedback effects and draw inference from long-term equilibrium perspective, we report summary measures of direct, indirect and total impacts as well as spatial partitioning of these impacts. To draw reliable statistical inference from the sampling theory perspective on these impacts is not a straightforward task as they are complicated, non-smooth functions of underlying model parameters as stated in (11) and (12). On the other hand, a simulation-oriented Bayesian approach would have been relatively straightforward if the posterior distribution of the underlying parameters were easy to sample from. We apply the asymptotic theory in Kwan (1999) to interpret the asymptotic normal distribution of the GMM estimator as an approximate posterior distribution, which in turn allows us to use simulation method to compute the posterior distribution of various impact measures and their spatial partitioning. More specifically, a random draw from the approximate posterior distribution of the parameter vector $\theta = (\tau, \rho, \beta, \gamma)$ is $\theta_d = P\delta + \hat{\theta}$, where $\hat{\theta}$ is the value of the GMM estimate; P is the lower-triangular Cholesky decomposition of the asymptotic covariance matrix of the GMM estimator; and δ is a vector containing random draws from a standard normal distribution. Each draw will result in one parameter combination for calculating impacts based on equations (8), (9) and (10). Based on 5000 random draws, we can then compute very accurate estimate of the moments and percentiles of the posterior distribution of the impacts.

Table 3 reports the marginal posterior distributions of direct, indirect and total impacts for the two proxies of FDI penetration. Both posterior means of direct impact for FDI employment share and sales income share are negative, suggesting FDI presence in a specific county is likely to generate negative impacts on domestic private firms in the same county through taking over market share and better employees from local firms. The negative impact from market stealing may pass through neighboring counties, as suggested by the negative indirect spillovers captured by FDI sales income share. The knowledge spillovers through labor turnover, however, generate positive and significant inter-regional spillovers. The inter-regional spillovers outweigh the intra-regional spillovers in magnitude, resulting in positive average total FDI spillovers through labor market in the long-term.[12]

[12] More precisely, assume that FDI employment share in all counties increases by 10% of the sample mean (i.e., 0.111×10% = 0.011, see summary statistics in Appendix D), domestic private firms' TFP on average would decrease by 0.844% (-0.768×0.011×100) due to direct impact from this increase in FDI presence in the exact same county they are located. Domestic private firms' TFP on average would increase by 27.917% (25.379×0.011×100) due to indirect spillovers from the increase in FDI presence in their neighboring counties, after accounting for impacts from spatial feedback loops. Indirect spillovers outweigh the direct spillovers, leading to an overall increase of 27.072% (24.611×0.011×100) in TFP. On the other hand, if FDI sales income share in all counties increases by 10% of the

Table 3
Marginal posterior distributions of cumulative spillovers.

			Percentile				
	mean	sd	5%	25%	50%	75%	95%
FDI: employment share							
Direct spillovers	-0.768	1.153	-2.649	-1.562	-0.774	-0.021	1.144
Indirect spillovers	25.379	15.875	1.300	14.596	24.362	34.747	52.458
Total spillovers	24.611	15.648	1.089	13.841	23.601	33.796	51.268
FDI: sales income share							
Direct spillovers	-3.419	0.949	-4.982	-4.063	-3.432	-2.783	-1.849
Indirect spillovers	-41.129	18.909	-75.784	-51.474	-39.426	-27.895	-14.556
Total spillovers	-44.548	18.773	-78.448	-54.815	-42.654	-31.242	-18.124

Note: All statistics reported are results from 5,000 simulations.

Table 4 reports statistics for spatially partitioned impacts based on 5,000 simulations. As discussed in previous section, these summary partitioned measures not only describe the decay pattern of spillovers but also decompose them into narrow and wide geographic scopes. The results indicate that, for both of the two FDI proxies we adopted in this study, the intra-regional (direct) spillovers and inter-regional (indirect) spillovers present very different spatial decay pattern. On average, the intra-regional spillovers become almost negligible even in first-order feedback loop (impact from immediate neighbors with $\boldsymbol{W}^1$ being the weight). Notice that the magnitudes of first-order feedback in both cases are very small, implying that the penetration of FDI in a specific county on average will affect its immediate neighbors, which in return will generate some but almost negligible feedback impacts to the domestic private firms in this specific county. The magnitudes of inter-regional spillovers, however, are still quantitatively significant in the third-order feedback loop and could even extend to the fourth-order feedback loop. These results suggest that, among spatial feedback loops, the negative intra-regional FDI spillovers decay very fast and are almost bounded locally while the inter-regional FDI spillovers present slower decay pattern and could extend to higher order neighbors.

As spatially partitioned impacts decompose impacts into narrow and wide geographic scopes, the results in Table 4 also filter and identify spillovers that pass through these scopes and reach domestic firms in different manners. As discussed in previous section, spillovers through labor turnover channel could be both negative (poaching local talents) and positive (knowledge spillover) that are operative at the same time. Knowledge spillovers, nevertheless, should have wider

sample mean (i.e., 0.127×10% = 0.013), the associated direct spillovers among to a 4.445% decrease in TFP and an even larger decrease of 53.468% due to indirect spillovers. The total spillovers in this case amount to 57.912% decrease in TFP of domestic private firms.

geographic scope than poaching effect. The results in Table 4 seem to have disentangled these two impacts successfully. The negative impacts in narrow scope (direct spillovers) are due to poaching whereas the positive knowledge spillovers become dominant in wider scope (indirect spillovers). Negative market stealing effect as captured by sales income share is negative in both narrow and wide scopes, which is consistent with our conjecture that such spillover has no boundary in a rapidly integrated market.

Table 4

Marginal posterior distributions of partitioned spillovers.

		FDI presence: Employment share		FDI presence: Sales income share	
		mean	sd	mean	sd
Direct spillovers	zero-order feedback loop (W^0)	-0.7677	1.1595	-3.4032	0.9508
	first-order feedback loop (W^1)	0.0082	0.0069	-0.0130	0.0092
	second-order feedback loop (W^2)	0.0012	0.0015	-0.0025	0.0026
	third-order feedback loop (W^3)	0.0003	0.0007	-0.0006	0.0012
	fourth-order feedback loop (W^4)	0.0001	0.0006	-0.0002	0.0010
Indirect spillovers	zero-order feedback loop (W^0)	18.1183	10.5059	-27.9471	10.5900
	first-order feedback loop (W^1)	4.9941	4.2375	-9.0740	6.1350
	second-order feedback loop (W^2)	1.8321	2.2087	-3.3481	3.5139
	third-order feedback loop (W^3)	0.5282	1.1982	-0.9770	2.0348
	fourth-order feedback loop (W^4)	0.1625	1.0769	-0.3070	1.9256
Total spillovers	zero-order feedback loop (W^0)	17.3505	10.1066	-31.3503	10.4028
	first-order feedback loop (W^1)	5.0023	4.2444	-9.0870	6.1442
	second-order feedback loop (W^2)	1.8332	2.2102	-3.3506	3.5165
	third-order feedback loop (W^3)	0.5285	1.1989	-0.9776	2.0360
	fourth-order feedback loop (W^4)	0.1626	1.0775	-0.3072	1.9267

Note: All statistics reported are results from 5,000 simulations.

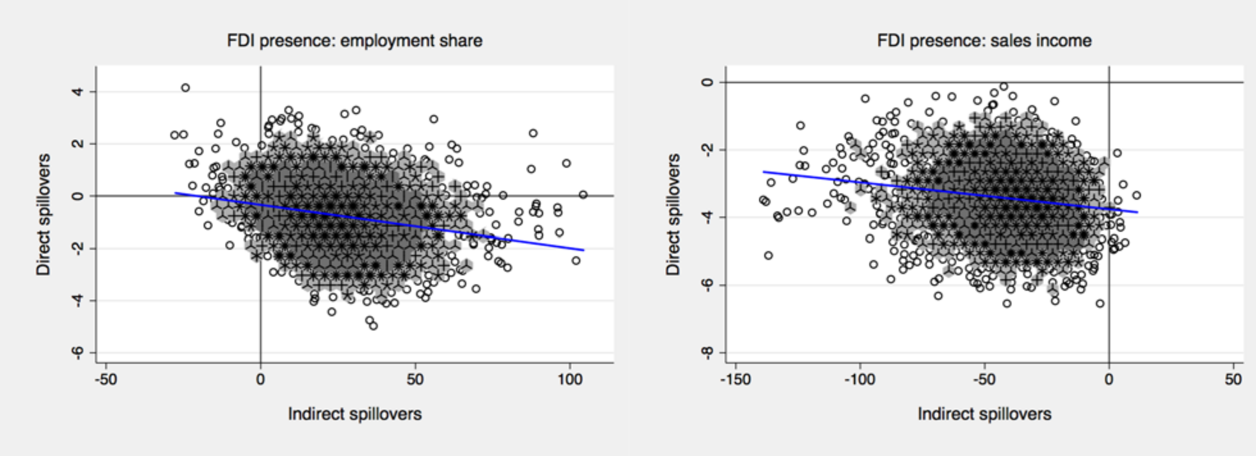
In Table 5, we present the posterior probabilities of spillovers for both FDI employment share and FDI sales income share based on simulated data. This table describes the most likely outcome when various spillover channels operate at the same time. In each 2 by 2 table, based on 5,000 simulations, we calculate the probabilities of positive or negative spillovers for both direct and indirect impacts. The statistics reveal that the probabilities are not evenly distributed in all four scenarios. As for FDI employment share (Panel A), the probability for positive indirect and negative direct impacts is the highest (0.7292). This suggests that, through poaching or cherry picking local employees, MNEs generate locally bounded negative effect on the productivity performance of domestic firms located in the same county. Domestic firms located in neighboring counties, on the other hand, are likely to benefit from FDI knowledge spillovers which diffuse beyond borders. As for FDI sales income share (Panel B), the probability for both negative direct and indirect impacts outcome is the highest (0.9886) among all four scenarios, suggesting a sweeping market stealing effect that adversely affects domestic firms irrespective of geographical distance.

Fig. 4 depicts density-distribution sunflower plots. With the aid of these plots we are able to display density of bivariate data (direct and indirect impacts) in a two dimensional graph. As presented in the figure, for FDI employment share, high- and medium-density regions are mainly located in the quadrant of negative direct spillovers and positive indirect spillovers. For FDI sales income share, high- and medium-density regions are mainly located in the quadrant where both direct and indirect spillovers are negative. These results are consistent with the posterior probabilities presented in Table 5. An additional interesting finding is that, as shown by the fitted line, for both FDI employment share and sales income share, direct and indirect spillovers are significantly and negatively correlated; with slope coefficients are -0.0165 and -0.0080 respectively. These negative correlations, as well as the fact that the one for FDI employment share is much stronger (more than doubled compared to FDI sales income share), remain puzzling to us and warrant further investigation in future research.

Table 5
Posterior probabilities.

Panel A: FDI Presence: Employment Share			
		Indirect spillovers	
		Negative	Positive
Direct spillovers	Positive	0.0216	0.2302
	Negative	0.0190	**0.7292**
Panel B: FDI Presence: Sales Income Share			
		Indirect spillovers	
		Negative	Positive
Direct spillovers	Positive	0	0.0078
	Negative	**0.9886**	0.0036

Note: All statistics reported are results from 5,000 simulations.



Source: Authors’ calculation based on simulated data.

Fig. 4. Joint posterior distribution of direct/indirect cumulative spillovers.

5. Conclusions and Policy Implications

The diffusion and materialization of FDI spillovers are neither automatic nor universal; instead, they are affected by various simultanuously operating factors drawn from both economic and geographical dimensions. These factors are of different geographic scopes and reach domestic firms in different manners. How to identify and then quantify these resulting impacts separately remain a challenging yet important issue in the literature. We investigate in this paper the geographic extent of various FDI spillover channels and their diffusion pattern by means of a large panel data set of Chinese manufacturing firms and their location information down to county level. In particular, geographical distance is used to disentangle spillovers with different scopes from a complex overall effect with spatial feedback loops. Working with a spatiotemporal panel regression model, we are able to identify and uncover the sign, the magnitude, and the geographic attenuation pattern of FDI spillover effects from different channels.

We find that intra-regional spillovers tend to be negative, irrespective of spillover channels. Inter-regional spillovers, on the other hand, could be negative or positive depending on spillover channels. These findings are consistent with common belief about the sign and the scope of FDI spillovers. Given that it is relatively costly to poaching local talents from distant domestic firms whereas barries and communication cost for knowledge spillovers have been significantly reducing, our method identifies negative poaching impact in narrow scope and positive knowledge spillovers in wider geographical scope. Our result also documents that negative market stealing effect does not have boundary and could extend from narrow scope to wide scope via rapidly integrated market.

What is the policy take-away of this paper? In order to attract FDI and, most importantly, to facilitate domestic firms to learn from nearby foreign firms with advanced technology, China's government has been providing incentive package for MNCs, as well as adopting place-based policy since the early 1990s. Corresponding strategies include tax holiday or reduction, job-creation subsidies, preferential loan to FDI, special economic zones and similar schemes, and construction of industrial facilities (land and infrastructure are subsidized) provided by both central and local governments. Many local governments also compete with their neighboring governments in this regard, which partially results in severe strategic tax competition and 'race to the top / race to the bottom' problem (Yao and Zhang, 2008). One major findings of this paper is that domestic firms mainly benefit from FDI presence in their neighboring regions, whereas FDI direct impacts to a specific location itself are likely to be negative. Consequently, as far as a particular local government is of concern, it is important to rethink about the strategic tax competition approach for attracting FDI, as the benefit from doing so may not be as large as commonly believed. A better strategy for local governments is to cooperate with each other to provide better environment for both MNCs and domestic firms, such as providing better infrastructure for transportation across regions, lower regional tariff for capital and labor, and fair tax treatment for both MNCs and domestic firms. To this end, coordination between local governments would be of utmost importance.

In view of the fact that place-based FDI policy has been widely implemented in many developing countries in a top-to-bottom manner, the empirical evidence documented in this paper should not only be relevant to those who are interested in China's FDI policy but also relevant for refining aggregate strategic response to FDI presence for developing countries in general. We also believe that incorporating industry dimension in a further study would be necessary.[13] Given the salient economic agglomeration and industrial clustering phenomena at the regional level of China, sub-industry evidence would provide vital focused reference for local governments to make their regional specific FDI policy. We leave it to future research to determine and demonstrate empirically these sub-industry results.

[13] We would like to thank an anonymous reviewer's insightful comment and suggestion on this point.

Appendix A. Ownership structure and their corresponding portions in NBS-CIE database

		Domestic Firms											Foreign Firms				Sino-Foreign Joint Ventures (JVs)				Others	
		Privates								SOEs												
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8): sum of (1) to (7)	(9)	(10)	(11): (9) + (10)	(12)	(13)	(14)	(15): (12) + (13) + (14)	(16)	(17)	(18)	(19): (16) + (17) + (18)	(20)	
Year	No. of Firms	Pure Privates	Other Domestic Private Firms	Collective Enterprise	Joint-Stock Enterprise	Associated Economics	Limited Liability Company	Corporation Limited Enterprises	All Domestic Privates	Pure SOEs	SOEs-Domestic JVs	SOEs	Pure F-type FDI	Pure HMT-type FDI	Joint Ventures between F and HMT	FDI	Sino-Foreign JVs	Sino-HMT JVs	Other Sino-Foreign JVs	Sino-Foreign JVs	Undefined	Total: (8) + (11) + (15) + (19) + (20)
1998	102830	11.25	3.36	30.44	4.44	1.54	2.49	1.18	54.70	16.48	5.87	22.35	2.84	3.88	0.03	6.75	6.43	6.76	0.27	13.46	2.74	100
1999	111715	13.17	4.53	27.44	4.48	1.43	3.17	1.39	55.60	14.80	5.96	20.76	3.13	4.97	0.04	8.14	5.89	6.60	0.25	12.75	2.76	100
2000	110090	19.10	5.80	22.25	4.08	1.19	4.27	1.47	58.17	11.99	5.34	17.33	3.41	5.50	0.05	8.96	5.77	6.84	0.23	12.85	2.69	100
2001	125235	26.56	7.86	16.84	3.66	0.95	5.57	1.52	62.96	8.97	4.32	13.29	3.83	5.82	0.05	9.70	5.44	6.19	0.22	11.85	2.21	100
2002	136163	32.63	9.12	13.26	2.84	0.71	5.98	1.52	66.06	7.26	3.65	10.90	4.28	5.69	0.07	10.04	5.34	5.36	0.20	10.89	2.10	100
2003	153585	37.94	10.95	9.38	2.22	0.52	6.46	1.47	68.95	5.30	2.70	8.00	4.72	6.35	0.05	11.12	5.01	4.89	0.16	10.06	1.88	100
2004	219335	44.28	11.83	5.59	1.56	0.31	7.70	1.21	72.47	3.21	1.76	4.97	5.72	6.58	0.05	12.36	4.79	4.11	0.13	9.03	1.18	100
2005	218401	44.93	13.76	4.47	1.28	0.26	7.44	1.19	73.34	2.44	1.37	3.81	5.97	6.88	0.05	12.91	4.41	3.68	0.10	8.19	1.76	100
2006	239352	47.68	14.12	3.75	1.36	0.21	7.08	1.01	75.21	1.89	1.09	2.98	5.89	6.70	0.05	12.64	4.09	3.31	0.09	7.49	1.69	100
2007	266311	48.43	16.27	2.96	1.14	0.17	6.90	0.92	76.78	1.42	0.86	2.28	5.92	6.55	0.05	12.52	3.67	2.91	0.09	6.67	1.75	100

Note: Authors' calculation based on NBS-CIE database. This table is produced based on total record of 503,079 firms with 1,683,017 observations after we clearn up the dataset by following the suggestions provided in Brandt et al. (2012). All statistics reported are results after data cleaning. A firm's ownership structure is determined by its source and structure of Paid in Capital and their registered type. 'Pure' means the Paid in Capital is 100% from the corresponding source; for instance, 'Pure Private' means all the Paid in Capital of these firms are from private sector. 'HMT' denotes foreign firms from Hong Kong, Macau, and Taiwan. 'F' denotes foreign firms from countries / regions other than Hong Kong, Macau, and Taiwan.

Appendix B. Data and variable

In this paper we employ data from the annual census of above-size manufacturing firms conducted by the National Bureau of Statistics (NBS) of China (known as the Chinese Industrial Enterprises Database, NBS-CIE database henceforth) from 1998 to 2007. Our data cleaning process follows closely the suggestions provided in Brandt et al. (2012 and 2014). For this study, we drop firms with employment (personal engaged) below 8 workers and firms with negative nominal capital stocks, paid-up capital, sales revenue, value added, or intermediate inputs. We use industry concordances provided by Brandt et al. (2012) as consistent industry identifier throughout the sample period. Nominal input and output data are deflated by input and output deflators at 2-digit industry level (1998 = 100), which are also obtained from Brandt et al. (2012).

Variables for capital stock in the original NBS-CIE database could not serve as good measures for capital input. Firms in the database do not report fixed investment. Fixed capital stock data are reported as the sum of book values in different years' price level, which cannot be used directly for TFP estimation. We thus compute a real capital stock series using the perpetual inventory approach proposed in Brandt et al. (2012 and 2014).

We first make use of the capital stock data reported in 1993 annual enterprise survey and in 1998 NBS-CIE database to estimate average growth rate of the nominal capital stock between 1993 and 1998 at province by industry (2-digit) level.[14] By using this estimated growth rate (g), together with capital stock at original purchase price ($fa^{initial}$) and the firm's age (age), we calculate the firm's initial nominal capital stock (nk_0) in the establishment year, $\boldsymbol{nk_0 = fa^{initial} / (1+g)^{age}}$.[15] The firm's real capital stock in the establishment year ($\boldsymbol{rk_0}$) is obtained by deflating nk_0 using investment deflator (1998 = 100) constructed by Perkins and Rawski (2008).[16] Nominal capital stock data after the establishment year is then calculated by using the estimated growth rate (g). Assuming a 9% depreciation rate, the real capital stock data in 1998 (or the firm's first year in the sample) is then calculated by using perpetual inventory method and Perkins and Rawski deflators.[17] Real capital stock after 1998 (or after the firm's first year in the sample) is calculated by following

[14] The 1993 nominal capital stock data is made available in Brandt et al. (2012). As it is the earliest comparable data available, this paper, along with most other studies using NBS-CIE database, adopts 1993 as the initial year in applying the perpetual inventory method.

[15] Following Brandt et al. (2012, 2014), we assume that, for firms with establishment year earlier than 1978, their experience before 1978 have negligible impact on the capital stock in 1998 and thus reset the establishment year for these firms to 1978.

[16] Deflators up to 2006 are reported in Brandt et al. (2012). We thank Yifan Zhang for confirming our calculation of deflator for 2007 by following the chain-link approach in Perkins and Rawski (2008).

[17] The choice of 9% depreciation rate follows Perkins and Rawski (2008) and Brandt et al. (2012). This depreciation rate is used in most other studies for constructing capital stock using NBS-CIE database.

the same perpetual inventory method with 9% depreciation rate but use the first difference in firm's nominal capital stock measured at original purchase prices as fixed investment for each year.

Appendix C. Constructing county-level TFP from firm-level data

County-level TFP in Eq. (4) is constructed as the weighted average of firm-level $\ln(TFP)s$ with the weights being the value added shares of the firm in the underlying county in each year. Specifically, TFP_{it}, for county i, in year t is constructed as

$$TFP_{it} = \frac{va_{jit}}{\sum_{j\in i} va_{jit}} \ln(TFP)_{jit}$$

where va_{jit} denotes the year t's value added for firm j located in county i.

Our estimation procedure for firm-level productivity in logarithm, $\ln(TFP)$, largely follows the algorithm initiated by Olley and Pakes (1996) and then further developed by Levinsohn and Petrin (2003) with the aim to tackle the potential endogeneity problem arising from potential correlation between input levels and unobserved firm-specific productivity shocks. This algorithm is commonly referred as "proxy variable approach" in the literature (Amit et al., 2008). We nevertheless do go beyond this conventional approach to incorporate some new developments in the literature, which are mainly drawn from Ackerberg et al. (2006), Melitz and Levinsohn (2006) and De Loecker and Warzynski (2012). Given that Levinsohn and Petrin (2003) (LP hereafter) algorithm has become a standard method in the literature and has been reintroduced in many studies, in the following we should focus on discussing the places in our procedure that have departed from conventional LP routine.[18]

The first departure from the conventional LP routine is in the functional form used for production function. Instead of using Cobb-Douglas production function, we adopt a translog production function that includes all the (logged) inputs and their second order polynomial terms, i.e., (logged) inputs squared and interaction terms between all (logged) inputs. This departure avoids the assumptions of 1) perfect substitution between production factors; 2) constant output elasticity across firms and over time; and 3) perfect competition in the production factors market across firms and over time, which are all too restrictive to be valid in the empirical application (De Loecker and Warzynski, 2012). More specifically, in a specific industry, for a value added translog production function we have

[18] For more comprehensive discussion on both theoretical and empirical issues of this topic, the interested reader is referred to Ackerberg et al. (2006), Melitz and Levinsohn (2006), Van Beveren (2012), and De Loecker and Warzynski (2012).

$$va_{jt} = \beta_l l_{jt} + \beta_k k_{jt} + \beta_{ll} l_{jt}^2 + \beta_{kk} k_{jt}^2 + \beta_{lk} l_{jt} k_{jt} + \psi_{jt} + \varepsilon_{jt}$$

where va_{jt}, l_{jt}, k_{jt}, and ψ_{jt} are respectively firm j's value added, labor input, capital input, and unobserved productivity component at time t. All variables are in logarithm. ε_{jt} is an error term that is assumed to be uncorrelated with all input choices. Firms will make input decisions based on their productivity; thus, productivity component ψ_{jt} is correlated to input choices. Since data for ψ_{jt} usually is not available, conventional method like OLS will lead to bias estimation, unless a valid proxy for productivity could be included in the regression as control variable.

To proxy for productivity, we follow Levinsohn and Petrin (2003) to rely on material demand function, which assumes that demand for the intermediate input, m_{jt}, is a monotonous (increasing) function of ψ_{jt}, i.e., $m_{jt} = m_t(k_{jt}, \psi_{jt})$, where both k_{jt} and ψ_{jt} are state variables based on which firms make their input decisions. The productivity component, ψ_{jt}, is then constructed by inverting this demand function to get $\psi_{jt} = h_t(m_{jt}, k_{jt})$.[19]

As the second departure from the conventional LP method, we explore and include additional state variables and other demand conditions in $h_t(.)$. This departure follows Melitz and Levinsohn (2006) and De Loecker and Warzynski (2012) with an aim to incorporate more variables that potentially affect firms' optimal input demand choice. Failing to do so would weaken the validity of using intermediate inputs as a proxy for productivity. Consequently, we include in $h_t(.)$ a vector z_{jt}, i.e., $\psi_{jt} = h_t(m_{jt}, k_{jt}, z_{jt})$, where z_{jt} includes a dummy for export status (equals 1 if export value is positive), a dummy for R&D status (equals 1 if R&D expenditure is positive), a survival propensity score described in Olley and Pakes (1996), and a demand condition derived in Melitz and Levinsohn (2006) to allow for product heterogeneity and imperfect competition.[20]

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[19] Included in $h_t(.)$ are $m_{jt}, m_{jt}^2, k_{jt}m_{jt}$, and $k_{jt}m_{jt}^2$.

[20] NBS-CIE database, like many other firm level datasets, does not report either physical output or physical attributes for this output. A common solution is to use industry-level input and output deflators to deflate nominal terms. If firms in an industry produce homogeneous goods, an assumption that is implicitly assumed in the conventional LP routine, the above approach could yield a valid proxy for the unobserved physical output. However, since firms are likely to produce goods that are differentiated, firm level prices will fluctuate relative to the industry price index and hence break the link between deflated sales and physical output. Both Van Beveren (2012) and De Loecker and Warzynski (2012) illustrate the potential bias in the process of production function estimation, and thus in productivity, if this problem is not addressed appropriately. Under some modest assumptions, Melitz and Levinsohn (2006) show that including a demand condition, $[(r_t - \tilde{p}_t) - n_t]$ (where, everything in logarithm, $r_t - \tilde{p}_t$, is total industry deflated sales and n_t is the number of firms in the industry) in a conventional deflated production function is sufficient enough to eliminate the impact of unobserved firm level prices.

The final departure from LP routine is that, instead of identifying labor coefficient in a first stage, we identify all the coefficients at once and in the final stage. Ackerberg et al. (2006) illustrate that identifying labor coefficient in the first stage of LP routine is not possible. Given the assumption that decision on labor and intermediate inputs are both made based on state variables k_{jt} and ψ_{jt}, it is impossible to simultaneously identify both a non-parametric function of k_{jt} and ψ_{jt} and the labor coefficient together since labor input is also a function of k_{jt} and ψ_{jt}.

To be precise, in a first stage regression, we run

$$va_{jt} = \phi_t(l_{jt}, k_{jt}, m_{jt}, z_{jt}) + \varepsilon_{jt}$$

from where we obtain estimates of expected output, $\hat{\phi}_{jt}$, a proxy of productivity, $\psi_{jt}(\tilde{\beta})$, and an estimated for ε_{jt}. The expected output is given by

$$\hat{\phi}_{jt} = \tilde{\beta}_l l_{jt} + \tilde{\beta}_k k_{jt} + \tilde{\beta}_{ll} l_{jt}^2 + \tilde{\beta}_{kk} k_{jt}^2 + \tilde{\beta}_{lk} l_{jt} k_{jt} + \hat{h}_t(m_{jt}, k_{jt}, z_{jt})$$

and the proxy of productivity is computed as

$$\psi_{jt}(\tilde{\beta}) = \hat{\phi}_{jt} - \tilde{\beta}_l l_{jt} - \tilde{\beta}_k k_{jt} - \tilde{\beta}_{ll} l_{jt}^2 - \tilde{\beta}_{kk} k_{jt}^2 - \tilde{\beta}_{lk} l_{jt} k_{jt}$$

where $\tilde{\beta}$ is a vector of coefficients from the first stage regression.

Following De Loecker and Warzynski (2012), we rely on the law of motion for productivity, i.e., $\psi_{jt} = \delta_t(\psi_{jt-1}, z_{jt-1}) + \xi_{jt}$, to identify all the coefficients in the second stage. By non-parametrically regressing $\psi_{jt}(\tilde{\beta})$ on $\psi_{jt-1}(\tilde{\beta})$ and z_{jt-1}, we obtain the innovation to productivity, $\xi_{jt}(\tilde{\beta})$. The following moment conditions are then used to estimate coefficients in the production function

$$E\left(\xi_{jt}(\tilde{\beta}) \begin{pmatrix} l_{jt-1} \\ k_{jt} \\ l_{jt-1}^2 \\ k_{jt}^2 \\ l_{jt-1} k_{jt} \end{pmatrix} \right) = 0.$$

Based on the estimated coefficients in this second stage, $\hat{\beta}$, firm-level $\ln(TFP)s$ are computed as $\ln(TFP)_{jt} = va_{jt} - \hat{\beta}_l l_{jt} - \hat{\beta}_k k_{jt} - \hat{\beta}_{ll} l_{jt}^2 - \hat{\beta}_{kk} k_{jt}^2 - \hat{\beta}_{lk} l_{jt} k_{jt}$.

Appendix D. Summary statistics at county level

			Percentile					
	Mean	Standard Deviation	5%	25%	50%	75%	95%	Obs.
TFP of Domestic Private Firms	2.6384	2.3566	0.1994	1.1455	2.2469	3.6115	6.3601	17187
FDI Presence: Employment Share	0.1112	0.1727	0	0	0.0320	0.1530	0.4968	18167
FDI Presence: Sales Income Share	0.1270	0.1987	0	0	0.0298	0.1726	0.5898	18167
SOEs Presence	0.3467	0.3300	0	0.0380	0.2464	0.6127	0.9876	18165
W * TFP of Domestic Private Firms	1.4648	0.6266	0.5139	0.9587	1.4327	1.9491	2.5028	18167
Space-time lagged TFP of Domestic Private Firms	1.3452	0.5966	0.4645	0.8608	1.2937	1.8077	2.3388	15519
W * FDI Presence: Employment Share	0.0664	0.0281	0.0229	0.0446	0.0650	0.0862	0.1133	18167
W * FDI Presence: Sales Income Share	0.0757	0.0299	0.0272	0.0531	0.0755	0.0997	0.1209	18167
W * SOEs Presence	0.1941	0.1010	0.0647	0.1129	0.1626	0.2699	0.3819	18165

Source: Authors' calculation based on NBS-CIE database.

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