Productivity spillovers among linked sectors

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ABSTRACT

This paper estimates the impact of inter-sectoral linkages on productivity at the sectoral level. An exhaustive Chinese panel data set for capital, infrastructure and a sectoral agglomeration index is linked with an economic distance matrix derived from inter-sectoral transactions. The latter matrix can replace the conventional geographic distance matrix from spatial econometrics. The impact through spillovers is mixed—the direct impact passing to related sectors and back to the initial sector itself, and the indirect impact arising from changes in all sectors. The results suggest that (1) economic growth in a sector is driven by spillovers among sectors that are linked through flows of goods and services; economic distance plays a more important role in stimulating productivity spillover than spatial distance; a shorter economic distance transmits a larger productivity spillover between sectors; (2) infrastructure spillover improves labor productivity in linked sectors; (3) agglomeration diseconomies can be partially reduced by infrastructure investment.

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1. Introduction

Industrialization is a process — productivity grows through dynamic change of the economic structure (Kuznets, 1971). At the risk of oversimplification, there are three different schools of thought regarding the nature of labor productivity. For analytical convenience, we designate them as the '*economic distance approach*', the '*infrastructure-driven approach*' and the '*geographic distance approach*'. The economic distance approach assumes that inter-sectoral linkages are the main determinant of industrial productivity. The economic sectors grow at different rates, as determined by resource endowments, consumer preferences, income elasticity of demand, and the path of economic growth. To the degree that sectoral transactions are nationally mobile and connected, the production of goods as inputs of other sectors, through their effects on production costs, may have important impacts on resource allocation and economic growth in the other sectors. Countries that rely on protecting 'infant sectors' with subsidies, quotas and tariffs to create structural reforms, face consumption distortions and a price wedge. So using *key sectors* to induce growth of related sectors and pull along the rest of the economy has gradually made its way onto the economic policy agenda under the heading of 'structural upgrading'. The effectiveness of such policy intervention depends crucially on the

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linkages among sectors. United Nations (2007) stated succinctly: 'Strengthening linkages is one of three most important dimensions that industrial policies in developing countries should be concerned with'.

In contrast, an alternative perspective, the geographic distance approach, has long existed. The geographic distance approach attributes *labor productivity* in a sector to *geographic agglomeration* (e.g. Martinez, Paluzie, & Pons, 2007). Part of its rationale comes from the new economic geography (NEG) theory that economic agents clustering in space have lower logistic costs than economic agents dispersing over space. However, high-tech sectors such as biotechnology, telecommunication, computer and electronics sectors do not necessarily rely on geographic agglomeration to transmit techniques or reduce logistic costs. This raises questions such as: Do upstream and downstream sectors have to relocate from one place to another to form geographic agglomerations such as core-periphery structures? Is there any spillover from sectors that are geographically distant but economically close? Are the externalities brought by spatial closeness larger than externalities brought by transactions?

Additionally, investigators such as Baffes and Shah (1998) attached more importance to the sectoral allocation of public investment as a major factor in the growth of labor productivity. Rather than allocating limited public capital equally in all sectors, governments can allocate public capital to key sectors such as transportation and telecommunications. Through the cooperation among different economic agents, the interaction of public and private inputs helps realize long-term sustainability of the manufacturing sector.

Based on the above-mentioned approaches, the goal of this paper is therefore to analyze the role of *inter-sectoral linkages*, *infrastructure and agglomeration* in sector-level productivity with a panel dataset of 31 provinces from all manufacturing sectors in China during the period 1996–2007. Accordingly, this paper creatively converts the trend of the changing inter-sectoral interactions into an *economic proximity matrix* and applies this matrix with spatial autocorrelation econometrics (Anselin, Varga, & Acs, 2000; Autant-Bernard & LeSage, 2011). This method is well-suited to this investigation for reasons described in Appendix A. We will test whether inter-sectoral dependence exists in the dependent variables, the independent variables or the error terms.

This paper extends current work on sectoral productivity in three important ways. The main finding is that the productivity of a sector is related to other sectors that provide its input or that use its output. This sectoral multiplier effect can be differentiated into *direct impact* (growth in a particular sector induces growth of other sectors and feedback to the sector itself) and *indirect impact* (growth in a particular sector supports net growth in the overall economy). The closer the economic distance among sectors, the higher the productivity spillover is. Economic distance is at least as important as geographic distance to the competitiveness of manufacturing sectors. Secondly, infrastructure spillovers through inter-sectoral linkages have acted as drivers of labor productivity growth. Thirdly, the low coefficient of sectoral agglomeration spillover is likely the result of agglomeration diseconomies, which can be offset partially by infrastructure spillover.

The remainder of this paper proceeds as follows. Section 2 summarizes literature relating to the channels through which inter-sectoral linkages promote productivity spillover, the control variables (infrastructure and agglomeration) and the estimation method (spatial econometrics). Section 3 presents a theoretical model and translates it into inter-sectoral econometric models that include the *inter-sectoral transaction matrix*. Section 4 explains the data. In Section 5, the effect of linkages on productivity is tested by selecting from a non-inter-sectoral panel model, an inter-sectoral Durbin model, an inter-sectoral lag model and an inter-sectoral error model, and by decomposition into *direct* and *indirect impacts*. The relationship between productivity spillover and economic distance is assessed. To compare economic distance with spatial distance, an empirical analysis of the spatial Durbin model is carried out in Section 6. The paper closes with a summary of key findings.

2. Literature review

This section starts with an introduction about the spatial econometrics that is closest to our method. Although there is no shortage of papers using spatial econometrics to estimate geographical linkages, our paper is the first to combine an economic matrix with spatial econometrics to investigate the economic linkages among sectors. The inter-dependencies among sectors through input–output linkages drive productivity spillover among sectors. The literature review also highlights two other issues which might contribute to productivity growth: infrastructure and agglomeration.

2.1. Linkages across sectors

Previous studies have embedded three Marshallian forces (Marshall, 1920) to classify inter-sectoral linkages into *labor linkage*, *customer–supplier linkage* and *technology linkage*. With regard to the riddle which inter-sectoral linkage contributes most significantly to productivity growth, different scholars give different answers: *labor linkage* (Dumais, Ellison, & Glaeser, 2002; Jofre, Marín, & Viladecans, 2011), *customer–supplier linkage* (Ellison, Glaeser, & Kerr, 2010), and *technology linkage* (Greenstone, Hornbeck, & Moretti, 2010). Nonetheless, these three linkages are NOT wholly independent from each other. *Customer–supplier* linkages are closely followed by labor sharing (Ellison et al., 2010) and trigger technology diffusion (Hauknes & Knell, 2009).

Customer–supplier linkage sets into motion a chain of flows that revolutionize the national production system. *Customer–supplier linkage* occurs when a sector provides its output to or buys input from other sectors. With the exchange of materials, technological and organizational innovations from upstream sectors are able to weave into production and be absorbed by the downstream sectors. Almost all other linkages can stem from *customer–supplier* linkages.

Many factors explain how a sector pulls along the linked sectors through input–output linkages. A short list of such causal factors includes:

(i) *cost reduction*: cost is reduced in two channels. On one hand, the improvement of productivity of downstream sectors will enlarge the market size for intermediate suppliers (upstream sectors), triggering entries of new upstream firms. The competition in upstream sectors reduces intermediate prices, which in turn decrease the procurement costs of the downstream sectors (Kranich, 2011). On the other hand, increasing demand by downstream sectors can lead to higher levels of specialization in upstream sectors, which eventually results in lower prices (Antonelli, 2008).

(ii) *pecuniary externalities*: the input–output linkages between FDI and domestic suppliers transmit pecuniary externalities. One out of every three FDI firms offers frequent financial support to suppliers (Jordaan, 2011).

(iii) *knowledge spillover*: the interaction of upstream producers and downstream producers develops a learning environment and facilitates knowledge spillover (Lewis, 2009; Hauknes & Knell, 2009; Kellogg, 2011). A sector, due to the existence of supplier–customer linkage, is likely to apply patented inventions obtained in other sectors (Scherer, 1984), and likely to use knowledge carried by innovative inputs from upstream producers to generate its own technological knowledge (Gehringer, 2010).

(iv) *the standardization of rules*: in the multi-sector ladder, no sector can set economic norms in isolation. The regulations are usually streamlined between supplier and customer sectors. Sectors have to adopt widely-accepted and balanced standards so as to increase transactions efficiency and market transparency and competition (Lewis, 2009).

(v) *the improvement of labor quality*: input output linkages are closely followed by similar labor needs (Ellison et al., 2010). Sharing labor among sectors improves the quality of labor and facilitates the growth of labor productivity (Young, 1995). Input output linkages reduce the gap between low-skilled and high-skilled workers.

(vi) *urbanization*: linkages generate geographic concentration between manufacturers and suppliers (Ellison et al., 2010), which is crucial to the emergence and growth of cities (Lewis, 2009).

Within this strand of literature, several methods have been used to estimate inter-sectoral productivity spillover. The first method is the nonlinear model. After comparing negative and positive effects of inter-sectoral linkages, Bravo-Ortega and Lederman (2005) pointed out that the development of non-agricultural sectors can cause the share of agriculture in national production to decline as the household spends less on food, and the technological innovations of related sectors spill over to the agriculture sector. The second method is patent citation. But patent citation is still an imperfect measure of intellectual spillover (Ellison et al., 2010). Knowledge sharing that occurs between customers and suppliers may be captured better by an input–output table than by patent citations (Porter, 1990).

The conventional methods pay little attention to the direct and indirect impacts of linkages. Inter-sectoral linkages have been recognized as economic distance (Dietzenbacher, Romero, & Bosma, 2005; Greenstone et al., 2010). To apply this notion empirically, we extract an economic transaction matrix where sectors are interwoven in the process of material exchange, and integrate this economic proximity matrix with the spatial Durbin model.

2.2. Productivity spillover

Productivity of a sector is influenced by its inputs, which are bought from other sectors. To estimate the productivity spillover, Bartelsman, Caballero, and Lyons (1994) built a model $y_{it} = \gamma x_{it} + \beta x_{it}^{a} + v_{it}$, where y_{it} is the growth rate in real value added in sector i, x_{it} is the growth rate in sector i's input, x_{it}^{a} is a weighted average of other sectors' activity, as measured by the growth rate of their inputs, and v_{it} is the growth rate of industry i's technology. They stated that the linkages between a sector and its customers are the most important factor in the transmission of externalities. Moretti (2004) noted that productivity spillover is strongly correlated with input–output and technology distances, and that spillover among sectors that are economically close is larger than spillover among sectors that are economically distant.

The inter-dependency of sectors also leads to productivity diffusion among sectors. Hayami (1991) and Crespi et al. (2008) used input–output data to prove the presence of productivity spillover among sectors due to the sharing of information. Holly and Petrella (2012) provided a useful modeling framework for productivity diffusion through factor demand linkages. In their RBC model, as an upstream sector increases productivity and lowers the price of its products, its downstream sectors can decrease the marginal cost of production and increase productivity and demand. This will in turn raise the productivity of the upstream sector since it is also a buyer of other sectors' supplies. The aggregate positive comovement between labor and productivity is driven, in particular, by a very strong positive complementary effect in those sectors which are most connected through input–output linkages.

2.3. Infrastructure spillover

It is widely agreed that public capital is of fundamental importance to aggregate productivity and should be included in production functions. 1% increase in infrastructure stock is associated with a 0.35% reduction in the poverty ratio (Jalilian & Weiss, 2004). Every $1 invested in public transportation generates approximately $4 in economic returns.[1] ICT investment accounted for

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[1] American Public Transit Association, "Facts at a Glance, 2012" http://www.publictransportation.org/news/facts/Pages/default.aspx (accessed: Dec. 2012).

0.3%–~0.8% of growth in per capita GDP in 1995–2001 in OECD members (Tambo, 2004). However, *infrastructure spillover* remains a relatively new area of research. It can be divided into spillover among regions and among sectors.

Infrastructure spillover among regions is defined as a phenomenon whereby public infrastructure in one region spills over to other regions and raises productivity in other regions. Boarnet (1998) included the infrastructure stock in neighboring counties in a county production function to prove that factors such as labor and private capital move in response to differences in public capital stocks. Pereira and Roca-Sagalés (2003) developed vector auto regressive (VAR) models to prove that public goods produce benefits outside the funding jurisdiction. Dembour and Wauthy (2009) reiterated that a 'local' infrastructure, as a public good, will inevitably see its benefits spill over to contiguous regions. Thus, they believed physical location in region A rather than B does not actually matter as far as spatial externalities are concerned.

Infrastructure spillover across sectors occurs when sectors in one region which have better infrastructure transact with sectors in other regions which have less infrastructure. Eberts and McMillen (1999) argued that both spatial proximity and physical infrastructure contribute positively to the productivity of firms in urban areas, and public infrastructure should be included as an input in the production function. Fernald (1999), using data for 29 sectors and public investment in roads during 1953–1989 in the U.S., observed that (1) when infrastructure investment decreases, sectors with higher vehicle shares experience larger slowdowns in productivity growth; (2) when infrastructure investment increases, productivity growth rises in vehicle-intensive sectors and falls in nonvehicle-intensive sectors. Innovation spillover occurs when there are large inter-sectoral linkages (Dietzenbacher, 2000; Swieczewska & Tomaszewicz, 2006). Changes in one sector's infrastructure share affect neighboring sectors. Duranton, Morrow, and Turner (2012) offered a complementary explanation that highways within cities bring sectors producing heavy goods comparative advantages. According to a report by Dahlman (2007), the Taiwan government implements "State-directed technological development strategy" by developing a strong supportive *technological infrastructure* such as technical information services and specialized public research institutes, and by creating *technological linkages*.

2.4. Sectoral agglomeration index

Sectoral agglomeration is also called industrial clustering (Ellison et al., 2010; Coniglio, Prota, & Viesti, 2011). Agglomeration indices can be used to quantify the inequality of a distribution across firms, people, or space and identify the mechanisms that drive employees and firms to co-locate geographically. The Herfindahl index measures industrial concentration. The generalized entropy index, the Theil index and special generalized entropy decompose total inequality into within region and between regions. To estimate the coefficient of regional industrial concentration, Gonda and Kyūi (1998) constructed the *CRIC* index which we will discuss in Section 3.1 and use the data of 23 sectors in 47 prefectures from 1980 to 1994 to identify the spatial mobility and developmental stages of manufacturing sectors. Based on employment data of Italian manufacturing sectors, Arbia (2001) concluded that the Gini coefficient, the Getis–Ord coefficient and Moran-I statistics can be used complementarily to capture spatial concentration of sectors. Using *K*-functions, Arbia, Espa, and Quah (2008) found that sectors tend to collocate to exploit technological and physical spillovers. Ellison et al. (2010) used the EG index, which is a modification of the spatial Gini index, to estimate coagglomeration of two sectors. Jofre et al. (2011) created an inter-sectoral weight index to assess each of Marshall's agglomeration mechanisms (using similar workers, a customer–supplier relationship, and knowledge spillover). While confirming the existence of all three mechanisms, they concluded that the most important mechanism is labor market pooling.

2.5. Spatial econometrics

Spillover among different units is widely studied by spatial econometric models. Case et al. (1993) used spatial econometrics to estimate the effect of one state's spending on that of its neighbors. Anselin et al. (2000) used a geographic matrix and sectorally disaggregated data and applied the methodology of spatial econometrics to estimate geographic spillover between university research and high technology innovations. Autant-Bernard and LeSage (2011) estimated R&D spillover across regions by using a spatial matrix. Cohen and Paul (2004) found public infrastructure investment related to manufacturing production is both enhanced and augmented by spatial spillover. Baicker (2005) also used spatial autocorrelation to estimate the extent to which a state's spending is influenced by the spending of its neighboring states.

Spatial econometric models are routinely created by adding a spatial weight matrix into theoretical models. Tian, Wang, and Chen (2010) added a spatial weight matrix into the technology variable of a Cobb–Douglas production function to create a spatial Durbin model which can capture technology spillover across provinces. Poudyal et al. (2009) defined a conceptual model: Life expectancy = f (socio-demographic factors; medical facility and risk factors; natural resource and environmental amenities), added a spatial matrix and rewrote this model into a spatial error model and, separately, a spatial lag model.

3. Model

To test the hypothesis that productivity at the sectoral level is driven primarily by inter-sectoral linkages, and secondarily by public investment on infrastructure, we first build an economic model which includes infrastructure and a sectoral agglomeration index, and then add an economic proximity matrix analogous to the spatial matrix from spatial econometrics.

3.1. Within-sector productivity

We start by building a sectorally disaggregated model so that inter-sectoral linkages can be added to it in Section 3.2.

$$Y/L = AC^{\gamma}(K/L)^{\alpha}\left(G/L_{region}\right)^{\beta} \tag{1}$$

where A is a positive constant. Y refers to sectoral industrial output. K denotes capital, and L labor in a sector. L_{region} is total labor in all sectors in a region. G is the region's infrastructure stock, and C is a sectoral agglomeration index. γ is the output elasticity of the sectoral agglomeration index and α is the output elasticity of capital. β is the output elasticity of infrastructure, measuring a sector's gain from the accumulation of infrastructure investment in a region.

To examine the hypothesis that public capital formation fosters productivity growth in linked sectors, we add infrastructure into the production function. As an external economy, infrastructure spreads knowledge and technology, reduces transaction costs, improves business and living environments and diminishes agglomeration diseconomies due to congestion, pollution or over-competition. It is a facilitator for agglomeration and thus can be a shift factor in the production function. For example, investment in the telecommunications sector can increase its demand for material from labor-intensive sectors such as the cable sector and the chemical material sector. Investment in 3G infrastructure helps the oil sector to discover resources and boosts the development of the automobile sector. Investment in the information sector makes it easier to publish ads, search suppliers and select logistic channels. Investments in water, power and gas make hotels more comfortable and travel safer, thereby facilitating the development of the tourism sector and the air transportation sector. By adapting Basile's (2011) definition of spatial externalities, inter-sectoral externalities can be defined as those growth enhancing elements of one sector that, in their nature of *public goods*, exert positive (or negative) effects on other sectors, with visible distance decay effects.

Our aim of assessing the contribution of sector-level agglomeration to economic growth leads us to incorporate a measure of sectoral agglomeration into the production function. C in Eq. (1) is a *CRIC* index (C index), which compares concentration and specialization both region-wide and industry-wide and compares the value for a particular sector with the value for all sectors:

$$C = (Csi/Cs)/(Cni/Cn)$$

where Csi denotes the variable value for sector s in province i, $i = 1,..., N$ ($N = 31$). Cs is the variable value of sector s in all provinces where $s = 1,...,S$ ($S = 36$). Cni refers to the variable value for all sectors in province i. Cn is the variable value for all sectors in all provinces. Take the sector 'Tobacco in Shanghai' as an example. C should be:

$$C = \frac{\frac{variable\ value\ of\ tobacco\ sector\ in\ Shanghai}{variable\ value\ of\ tobacco\ sector\ in\ China}}{\frac{variable\ value\ of\ all\ sectors\ in\ Shanghai}{variable\ value\ of\ all\ sectors\ in\ China}}.$$

Thus, the value of C represents the sectoral agglomeration degree of a particular sector in a region and indicates the extent of the deviation between a sector and a region. The closer to one, the more closely the national average is approached. When the value of the C index exceeds one, a sector accounts for a disproportionately high share of a region's amount of the variable value; the larger the value, the more concentrated a sector in that region compared to the nation overall. The C index compares overall agglomeration trends in a sector in the numerator, and compares overall agglomeration trends across all sectors and all regions in the denominator. Furthermore, to obtain a single value of C for sector s in region i, you have to compute the values of all sectors and the values of all regions. Economists assume a sectoral agglomeration index should be comparable across sectors (Duranton & Overman, 2002), separate spatial concentration from industrial concentration (Duranton & Overman, 2002) and require for the most complicated data (Kominers, 2007). The C index meets these criteria and is a satisfactory sectoral agglomeration measurement.

Taking the natural log of Eq. (1) and adding an error term, logged output per worker becomes:

$$\ln(Y/L) = \ln A + \alpha\ln(K/L) + \beta\ln\left(G/L_{region}\right) + \gamma\ln C + \varepsilon. \tag{2}$$

3.2. Economic linkages: inter-sectoral Durbin model (IDM)

Given that spillover among economically linked sectors is not necessarily tied to any particular geographic market, we adapt an $S \times S$ sectorally weighted matrix, as a measure of economic distance, into spatial econometrics to test the existence and strength of inter-sectoral dependency (see Appendix A). As with spatial autocorrelation, inter-sectoral autocorrelation occurs when the economic development of a sector is influenced by other sectors. Our model differs from Anselin et al. (2000), who use a

spatial matrix to research spatial externalities of innovation and R&D across sectors. The inter-sectoral Durbin model (*IDM*) is obtained by rewriting Eq. (2).

$$
\begin{aligned}
\ln(Y/L)_{sti} = {} & \delta_1 \sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti} + \alpha \ln(K/L)_{sti} + \beta \ln\left(G/L_{region}\right)_{sti} + \gamma \ln C_{sti} \\
& + \theta_1 \sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti} + \theta_2 \sum_{m=1}^{S} V_{sm} \ln\left(G/L_{region}\right)_{mti} + \theta_3 \sum_{m=1}^{S} V_{sm} \ln C_{mti} + \xi_s + \lambda_t + \varepsilon_{sti}
\end{aligned}
\tag{3}
$$

where δ_1 is the inter-sectoral autoregressive coefficient. θ_1, θ_2 and θ_3 are parameters. The model contains $s = 1, \ldots, S$ sectors in $i = 1, \ldots, N$ regions. The index $t = 1, \ldots, T$ refers to the time period. The subscripts represent the inter-sectoral interaction process, with sti denoting own sector and mti representing other sectors. $\ln(Y/L)_{sti}$, $\ln(K/L)_{sti}$ and $\ln(C)_{sti}$ are $NTS \times 1$ [2] vectors of natural logarithms of industrial output per worker, fixed assets per worker, and the sectoral agglomeration index for sector s in province i in year t. $\ln(G/L_{region})_{sti}$ is an $NTS \times 1$ vector of natural logarithms of infrastructure per worker in province i in year t. V_{sm} stands for an $S \times S$ inter-sectoral transaction matrix, whose value is based on product flows from sector s to sector m and refined by an algorithm described in Appendix A. IDM assumes that the dependent variable in sector s is influenced by the dependent and independent variables in related sectors. $\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$ is the transaction-weighted average of sectoral industrial output per worker in other sectors, capturing the inter-sectoral spillover. $\sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti}$, $\sum_{m=1}^{S} V_{sm} \ln(G/L_{region})_{mti}$ and $\sum_{m=1}^{S} V_{sm} \ln C_{mti}$ refer to the transaction-weighted averages of these variables from other related sectors. ξ_s is an $S \times 1$ vector of coefficients to be estimated, denoting sector specific effects. λ_t is an unobserved sectorally invariant effect, which is included to capture time-period heterogeneity (i.e. time-period fixed effects or time-period random effects). ε_{sti} is an $i.i.d(0, \sigma^2)$ disturbance.

The data set is a 3-dimensional $S \times T \times N$ matrix (sector, time and region) and needs be decomposed into a 2-dimensional matrix. After segmentation, the dimension of Eq. (3) can be reduced to:

$$
\begin{aligned}
\ln(Y/L)_{i_0} = {} & \delta_1 \sum_{j=1}^{N} V \ln(Y/L)_{i_0} + \alpha \ln(K/L)_{i_0} + \beta \ln\left(G/L_{region}\right)_{i_0} + \gamma \ln C_{i_0} \\
& + \theta_1 \sum_{j=1}^{N} V \ln(K/L)_{i_0} + \theta_2 \sum_{j=1}^{N} V \ln\left(G/L_{region}\right)_{i_0} + \theta_3 \sum_{j=1}^{N} V \ln C_{i_0} + \xi_{i_0} + \lambda_{i_0} + \varepsilon_{i_0}.
\end{aligned}
\tag{4}
$$

The inter-sectoral multiplier can be obtained by moving inter-sectorally lagged dependent variables from the right hand side to the left hand side of the equation:

$$
\begin{aligned}
\ln(Y/L)_{i_0} = {} & (I - \delta_1 V)^{-1} \left[\alpha \ln(K/L)_{i_0} + \beta \ln\left(G/L_{region}\right)_{i_0} + \gamma \ln C_{i_0} + \theta_1 \sum_{j=1}^{N} V \ln(K/L)_{i_0} + \theta_2 \sum_{j=1}^{N} V \ln\left(G/L_{region}\right)_{i_0} + \theta_3 \sum_{j=1}^{N} V \ln C_{i_0} \right] \\
& + (I - \delta_1 V)^{-1} \xi_s + (I - \delta_1 V)^{-1} \lambda_t + (I - \delta_1 V)^{-1} \varepsilon_{i_0}
\end{aligned}
\tag{5}
$$

where I is an $ST \times ST$ identity matrix and $(I - \delta_1 V)^{-1}$ is an inter-sectoral multiplier. $(I - \delta_1 V)^{-1} = I + \delta_1 V + \delta_1^2 V^2 + \delta_1^3 V^3 \ldots$. This expansion illustrates the second-order, third order, and higher-order impact. The impact is multi-directional. If sector A uses outputs from sector B as raw material and sector B buys outputs from sector C, production in sector A is influenced by both sector B and sector C. This multi-sector structure determines the magnitude and impact of the inter-sectoral spillover. A sector which has high backward linkages (uses output from other sectors as its input) and forward linkages (provides its output to other sectors as their input) generates a high multiplier effect.

Furthermore, spillover can be divided into a direct effect and an indirect effect. Partial differentiation of the dependent variable with respect to the independent variables yields:

$$
\begin{aligned}
\frac{\partial \ln(Y/L)}{\partial \ln(K/L)} &= Z_1(V) = (I - \delta V)^{-1}(\alpha + V\theta_1) \\
\frac{\partial \ln(Y/L)}{\partial \ln\left(G/L_{region}\right)} &= Z_2(V) = (I - \delta V)^{-1}(\beta + V\theta_2) \\
\frac{\partial \ln(Y/L)}{\partial \ln C} &= Z_3(V) = (I - \delta V)^{-1}(\gamma + V\theta_3)
\end{aligned}
\tag{6}
$$

(i). *direct impact*. The diagonal elements of $Z_1(V)$, $Z_2(V)$ and $Z_3(V)$ measure the impact of independent variables in sector s on the dependent variable in sector s. The direct impact includes the feedback loop where different sectors influence each other.

(ii). *indirect impact*. The off-diagonal elements of $Z_1(V)$, $Z_2(V)$ and $Z_3(V)$ measure the impacts of independent variables in other sectors on the dependent variable in sector s. The indirect impact needs to be interpreted in two ways. (a) How a change in explanatory variables (capital, infrastructure, sectoral agglomeration) in sector s would impact the dependent variable

(productivity) in neighboring sectors. (b) How a change in explanatory variables (capital, infrastructure, agglomeration) in all sectors would impact the dependent variable (productivity) in a typical sector s.

3.3. Implication of theory

Eq. (3) provides several valuable insights for the analysis of productivity spillover. The improvement of productivity in sector s might bring about positive impacts such as cost reduction, pecuniary externalities, knowledge spillover and the standardization of rules in sector m as stated in Section 2.1. Technologically cutting-edge sectors (e.g., computer and electronics sectors) or capital-intensive sectors (e.g., petroleum refining and tobacco) usually have higher productivity than the overall manufacturing average, while the lowest-paying sectors have less technology and capital.

Also, negative linkages might occur. Suppose sector s in region i improves its technology. Then sector s might increase its production efficiency and decrease its demand for raw materials, which would reduce its demand from supplying sectors. Output per worker should also be a function of economic distances among sectors. Specifically, the productivity in one sector is expected to be correlated with three groups of variables: the independent variables $(\ln(K/L)_{sti}, \ln(G/L_{region})_{sti}, lnC_{sti})$ in own sector, productivity in its related sectors $\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$, and linkages across sectoral boundaries $\sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti}$, $\sum_{m=1}^{S} V_{sm} \ln(G/L_{region})_{mti}$, and $\sum_{m=1}^{S} V_{sm} lnC_{mti}$. Omitting the second and third groups of variables may generate endogeneity bias, since these variables will be absorbed by the error term and the latter will be correlated with the included individual characteristics.

From this discussion, the hypotheses that could be tested using Eq. (3) are the following:

(A). $H_0^A: \delta = \theta_1 = \theta_2 = \theta_3 = 0$. When *hypothesis A* is correct, Eq. (3) is reduced to Eq. (2). The non-inter-sectoral regression does not consider linkages generated by inter-sectoral transactions between customers and suppliers. Thus, there is no relationship between a supplier and customer sector pair: sector s and sector m. Sector s is own sector, while sector m stands for its related sectors.

$$\frac{\partial E[\ln(Y/L)_{sti}]}{\partial \ln(K/L)_{sti}} = \alpha, \frac{\partial E[\ln(Y/L)_{sti}]}{\partial \ln(G/L_{region})_{sti}} = \beta, \frac{\partial E[\ln(Y/L)_{sti}]}{\ln(C)_{sti}} = \gamma$$

$$\frac{\partial E[\ln(Y/L)_{sti}]}{\partial \ln(Y/L)_{mti}} = 0, \quad \frac{\partial E[\ln(Y/L)_{sti}]}{\partial \ln(K/L)_{mti}} = 0, \quad \frac{\partial E[\ln(Y/L)_{sti}]}{\partial \ln(G/L_{region})_{mti}} = 0, \quad \frac{\partial E[\ln(Y/L)_{sti}]}{\ln(C)_{mti}} = 0$$

Under hypothesis A, we might conclude that there is no inter-sectoral effect and the explanatory variables in sector m do not affect its related sector s.

(B). $H_0^B: \theta_1 = \theta_2 = \theta_3 = 0$. When *hypothesis B* is correct, Eq. (3) is reduced to an inter-industrial autocorrelation lag model (*ILM*):

$$\ln(Y/L)_{sti} = \delta_2 \sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti} + \alpha \ln(K/L)_{sti} + \beta \ln(G/L_{region})_{sti} + \gamma \ln(C)_{sti} + \xi_s + \varepsilon_{sti}. \tag{7}$$

ILM indicates the possibility of a diffusion process (i.e. an event in one sector increases the likelihood of the same event occurring in related sectors). *If ILM is favored, the spillover in productivity comes directly from the productivity of other sectors, whether that productivity is caused by capital, infrastructure or technology in the other sectors.*

(C). $H_0^C: (\theta_1, \theta_2, \theta_3)' + \delta(\alpha, \beta, \gamma)' = 0$. When *hypothesis C* is correct, the restricted model is an inter-sectoral error model (*IEM*):

$$\ln(Y/L)_{sti} = \alpha \ln(K/L)_{sti} + \beta \ln(G/L_{region})_{sti} + \gamma \ln(C)_{sti} + \xi_s + \varphi_{sti}.$$

$$\varphi_{sti} = \rho_1 \sum_{m=1}^{S} V_{sm} \varphi_{mti} + \varepsilon_{sti} \tag{8}$$

where ρ is an inter-sectoral error coefficient to be estimated and φ_{mti} are the error terms for other sectors. *IEM* suggests the presence of omitted explanatory variables. IEM specifies an inter-sectoral autoregressive process for the error term to account for the inter-sectoral influence of unmeasured (or omitted) explanatory variables on productivity in the related sectors. *If the error model is preferred, the increase in productivity in one sector is transmitted from technology or other unmeasured residuals in the other sectors.* In Section 5, we will test these hypotheses and compare the performance of models based on LM tests and LR tests for these hypotheses.

3.4. Counterpart: spatial Durbin model (SDM)

Using spatial econometrics to capture spatial externalities is not the aim of this paper, but the technique provides some useful principles for uncovering the sectoral linkages. Elhorst (2010) presented test specifications for selecting among spatial panel data

models. He discussed spatial error autocorrelation, the determination of the variance–covariance matrix, the determination of goodness-of-fit measures and the best linear unbiased predictor. In spatial econometric models, the spatial weights contiguity matrix has zeros on the main diagonal, and the values will be '0' in positions where observational units are non-contiguous and '1' in positions where neighboring units are contiguous. A clear exposition of the spatial econometric models can also be found in Kalenkoski and Lacombe (2011).

Eq. (2) can be expressed in the form of the spatial Durbin model (SDM):

$$\ln(Y/L)_{its} = \delta_2 \sum_{j=1}^{N} W_{ij} \ln(Y/L)_{jts} + \alpha \ln(K/L)_{its} + \beta \ln\left(G/L_{region}\right)_{its} + \gamma \ln C_{its}$$
$$+ \theta_4 \sum_{j=1}^{N} W_{ij} \ln(K/L)_{jts} + \theta_5 \sum_{j=1}^{N} W_{ij} \ln\left(G/L_{region}\right)_{jts} + \theta_6 \sum_{j=1}^{N} W_{ij} \ln C_{jts} + \mu_i + \lambda_t + \varepsilon_{its} \tag{9}$$

where δ_2 is a spatial autoregressive coefficient. θ_4, θ_5 and θ_6 are parameters. The subscript *its* stands for own region, and subscript *jts* other regions. $\ln(Y/L)_{its}$, $\ln(K/L)_{its}$ and $\ln(C)_{its}$ are $NTS \times 1$ vectors of natural logarithms of industrial output per worker, fixed assets per worker, and sectoral agglomeration index for sector *s* in province *i* in year *t*. $\ln(G/L_{region})_{its}$ is an $NTS \times 1$ vector of natural logarithms of infrastructure per worker in province *i* in year *t*. W_{ij} is an $N \times N$ spatial matrix which denotes the connectivity of *i*-th (row) and *j*-th (column) elements and is time independent, location-based and binary-continuity. Its elements are 1 for adjacent neighbors and 0 otherwise. $\sum_{j=1}^{N} W_{ij} \ln(Y/L)_{jts}$, $\sum_{j=1}^{N} W_{ij} \ln(K/L)_{jts}$, $\sum_{j=1}^{N} W_{ij} \ln(G/L_{region})_{jts}$ and $\sum_{j=1}^{N} W_{ij} \ln C_{jts}$ refer to the averages of these variables from neighboring areas. Including spatially lagged independent variables when the coefficients on these variables are zero will not bias the estimates of the other parameters. μ_i is an unobserved temporally invariant effect, which is included to capture spatial heterogeneity (i.e. spatial fixed effect or spatial random effect). λ_t is an unobserved spatially invariant effect, which is included to capture time-period heterogeneity (i.e. time-period fixed effect or time-period random effect). ε_{its} is an $i.i.d(0, \sigma_1^2)$ disturbance.

The SDM nests the spatial lag model (SLM) and the spatial error model (SEM) as special cases that arise when common factor constraints are valid. When $\theta_4 = \theta_5 = \theta_6 = 0$, the SDM can be simplified to SLM. The first order SLM model of Eq. (2) can be written as:

$$\ln(Y/L)_{its} = \delta_2 \sum_{j=1}^{N} W_{ij} \ln(Y/L)_{jts} + \alpha \ln(K/L)_{its} + \beta \ln\left(G/L_{region}\right)_{its} + \gamma \ln(C)_{its} + \mu_i + \varepsilon_{its}. \tag{10}$$

When $(\theta_4, \theta_5, \theta_6)' + \delta_2(\alpha, \beta, \gamma)' = 0$, SDM can be simplified to SEM. Adding a spatially correlated error structure into Eq. (2) gives a spatial error model (SEM):

$$\ln(Y/L)_{its} = \alpha \ln(K/L)_{its} + \beta \ln\left(G/L_{region}\right)_{its} + \gamma \ln C_{its} + \mu_i + \varphi_{its}$$
$$\varphi_{its} = \rho_2 \sum_{j=1}^{N} W_{ij} \varphi_{jts} + \varepsilon_{its} \tag{11}$$

where φ_{its} is the spatial error component, ρ_2 is the spatial error coefficient and $\sum_{j=1}^{N} W_{ij} \varphi_{jts}$ is a spatial weighted error term. In SEM, a random shock in a region affects productivity in that region and additionally impacts its neighboring regions through the spatial transformation.

4. Data

The data covers the 1996–2007 period (12 years) and includes a total of 36 sectors (all manufacturing sectors) from 31 provinces of China. Data sources are summarized in Table 1.

Industrial output is adjusted by the ex-factory price index of industrial products by sector. *Capital stock* is adjusted by a price index of investment in fixed assets by region. The *spatial matrix* derives from the map of China at the provincial level. The *economic matrix* is derived from the sectoral transaction data in 1997, 2002 and 2005. Each of the 36 industrial sectors generates output to satisfy the final demand by other sectors. Each of the 36 sectors is both a buyer of inputs from and a supplier of output to other sectors (see Appendix A).

The *infrastructure* series is constructed from investments in transport, telecommunications (post, radio, TV, Internet, etc.), utilities (electricity, gas, water, environmental hygiene), and social infrastructure (public works, scientific research, and environment protection). Infrastructure has been deflated into a constant price by the price index for investment in fixed assets by region. The accumulation begins in 1949 when the data are first available. The perpetual inventory method was used. That is $G = I_t + G_{t-1}(1-d)$, where *t* is the time period. I_t denotes infrastructure investment in the current period, G_{t-1} is the accumulated infrastructure in province *i* in the previous period, and *d* denotes the depreciation rate. A depreciation rate of 5% was assumed (see evidence in Zhao & Hong, 2004).

We use sector-level data in each province to deal with both spatial econometrics and sectoral econometrics. The spatial regression includes spatial and time fixed effects to control for unobserved characteristics of regions. The intersectoral regression

Table 1
Data explanation.

Variable	Definition	Source
Y	Industrial output (RMB billion) for sector s in region i	drcne, cei
K	Capital stock (RMB billion) in sector s in region i	drcne, cei
L	Labor force (10 thousand) in sector s in region i	drcne, cei
L_{region}	labor in all sectors in a region	drcne, cei
G	Accumulated infrastructure (RMB billion) in a region	drcne, cei
N	Number of firms in sector s in region i	drcne, cei
C	Sectoral agglomeration measure	calculated
Csi	Variable value for sector s in region i	cei
Cs	Variable value for sector s in all regions	Calculated
Cni	Variable value for all sectors in region i	cei
Cn	Variable value for all sectors in all regions	Calculated

Notes: cei is the abbreviation for China Economic Information Network; drcne is the abbreviation for Development Research Center Information Network;missing data is complemented by data from China Statistical Yearbooks at the provincial level.

includes sectoral and time fixed effects to control for unobserved characteristics of sectors and time that might bias a simpler cross-sectional specification.

5. Estimates of economic distance

This section tests Eq. (3) against hypotheses A, B and C. If hypothesis A is correct, we should use a conventional panel data model, without interaction among sectors. If hypothesis B is accepted, we should select ILM. If hypothesis C is accepted, IEM is the best model. If hypotheses A, B and C are all rejected, IDM outperforms the others.

Table 2
Conventional model, inter-sectoral lag model, inter-sectoral error model and inter-sectoral Durbin model.

Eq. (3). Dependent variable: industrial output per worker $\ln(Y/L)$

	Without inter-sectoral interaction effects				With inter-sectoral interaction effects		
	Pooled OLS (1)	Inter-sectoral fixed effects (2)	Time fixed effects (3)	Inter-sectoral and time fixed effects (4)	Sectoral and time fixed effects (5)	Sectoral and time fixed effects bias-corrected (6)	Random sectoral effects, fixed time effects (7)
Intercept	0.83[a]						
$\ln(K/L)_{sti}$	0.55[a]	0.65[a]	0.45[a]	0.50[a]	0.51[a] (41.61)	0.51[a] (41.92)	0.51[a] (41.64)
$\ln(G/L_{region})_{sti}$	0.28[a]	0.26[a]	0.17[a]	0.16[a]	0.11[a] (7.86)	0.11[a] (7.95)	0.11[a] (7.85)
$\ln C_{sti}$	0.05[a]	0.08[a]	0.00[a]	0.03[a]	0.01[c] (1.62)	0.01[c] (1.63)	0.01 (1.60)
$\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$					0.08[a] (11.74)	0.09[a] (8.27)	−0.03[a] (11.74)
$\sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti}$					−0.02 (0.70)	−0.01 (−0.68)	0.02 (0.68)
$\sum_{m=1}^{S} V_{sm} \ln(G/L_{region})_{mti}$					0.04[a] (9.15)	0.05[a] (8.59)	0.07[a] (9.14)
$\sum_{m=1}^{S} V_{sm} \ln C_{mti}$					0.05[a] (3.32)	0.04[a] (3.17)	0.05[a] (3.33)
φ							0.08[a]
$\sigma 2$	1.42	1.14	0.75	0.49	0.61	0.60	0.61
R2	0.29	0.32	0.22	0.24	0.75	0.76	0.36
Corr^2					0.33	0.33	0.31
LR-lag	3412.68[a]	4152.82[a]	871.35[a]	977.87[a]	400.53[a]	333.71[a]	
rob. LM-lag	3547.70[a]	4202.83[a]	1035.75[a]	1070.20[a]			
Wald-lag					387.05[a]	452.46[a]	100.46[a]
LR-error	89.85[a]	153.89[a]	19.99[a]	9.82[a]	46.76[a]	11.81[a]	
rob. LM-error	224.86[a]	203.90[a]	184.40[a]	102.14[a]			
Wald-error					45.79[a]	42.49[a]	69.73[a]
Hausman							157.96[a]
LR		1818.03[a]	3484.05[a]				

[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

5.1. Hypothesis A (non-inter-sectoral models vs. inter-sectoral models)

Result 1. *From LR and LM tests, H_0^A has to be rejected. The inference based on conventional (non-inter-sectoral) regressions may generate an endogeneity bias since it omits spillover created during inter-sectoral transactions.*

To test whether the interdependencies among sectors influence productivity, we perform LR and LM tests with the null hypotheses $H_0^A : \delta = \theta_1 = \theta_2 = \theta_3 = 0$ on Eq. (3).

$$
\begin{aligned}
\ln(Y/L)_{sti} = {} & \delta \sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti} + \alpha \ln(K/L)_{sti} + \beta \ln\left(G/L_{region}\right)_{sti} + \gamma \ln C_{sti} \\
& + \theta_1 \sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti} + \theta_2 \sum_{m=1}^{S} V_{sm} \ln\left(G/L_{region}\right)_{mti} + \theta_3 \sum_{m=1}^{S} V_{sm} \ln C_{mti} + \xi_s + \lambda_t + \varepsilon_{sti}
\end{aligned}
\tag{3}
$$

Hypothesis A implies that a non-inter-sectoral model as Eq. (2) is the best model and that productivity is not influenced by intersectoral interaction. Different versions of Eq. (2) are reported in Columns 1 through 4 of Table 2. The selection of models using LM and LR tests is conceptualized by Baltagi, Egger, and Pfaffermayr (2006). The results in Column 2 (LR test 1818.03, with 36 degrees of freedom, p<0.01) indicate that the null hypothesis that the inter-sectoral fixed effects are jointly insignificant must be rejected. The results in Column 3 suggest that the null hypothesis that the time fixed effects are jointly insignificant must be rejected (LR 3484.05, with 372 degrees of freedom, p<0.01). Therefore, inter-sectoral panel models have to be used in order to tackle bias and to generate consistent estimates.

5.2. Hypothesis B (ILM VS. IDM) and hypothesis C (IEM VS. IDM)

Result 2. *From Wald and LR tests, H_0^B and H_0^C have to be rejected. IDM is considered to be more robust than ILM and IEM.*

The 5th–7th columns of Table 2 present results from fitting different versions of Eq. (3). By imposing hypothesis B and hypothesis C, we can compare inter-sectoral models (ILM, IEM and IDM), and compare fixed effect models and random effects models. The 5th column gives the results when using the direct approach, which will yield an inconsistent parameter. Column 6 gives unbiased coefficients when controlling for unobserved time-invariant inter-sectoral heterogeneity. Column 7 reports the results when μ_i is treated as a random variable rather than as a set of fixed effects.

Beginning with Column 5, we apply the common factor test and impose the theoretical constraint $H_0^B : \theta_1 = \theta_2 = \theta_3 = 0$ on Eq. (3). The results (*Wald-lag* 387.05, with 3 degrees of freedom [df], p<0.01; or *LR-lag* 400.53, 3 df, p<0.01) indicate that the hypothesis that the inter-sectoral Durbin model (IDM) can be simplified to the inter-sectoral lag model (ILM) must be rejected.

By the same token, we use *Wald-error* and *LR-error* to test the theoretical constraint $H_0^C : (\theta_1, \theta_2, \theta_3)' + \delta(\alpha, \beta, \gamma)' = 0$ on Eq. (3). The results (*Wald-error*: 45.79, 3 df, p<0.01; *LR-error*: 46.76, 3 df, p<0.01) indicate that the hypothesis that the inter-sectoral Durbin model can be simplified to the inter-sectoral error model (*IEM*) must be rejected. The rejection of the two null hypotheses implies that IDM constitutes a better representation of inter-sectoral dependence than ILM or IEM.

5.3. Selection between random effects and fixed effects

Result 3. *Hausman test and φ test prove that fixed effects are preferred to random effects.*

Column 7 of Table 2 shows *Hausman* test and φ value (φ^2 in Baltagi, 2005) which are measures of random effects. Random effects allow the estimation of time–invariant endogenous variables. However, estimators provided by random effects specification might be similar to those obtained with a fixed effects specification. The *Hausman* test (157.96.04, with 7 degrees of freedom [df], p<0.01) indicates that the random effects do not greatly differ from fixed effects. Another way to test the random effects model against the fixed effects model is to estimate the φ value, which measures the weight attached to the cross-sectional component of the data. The small φ value 0.08 with p<0.01 leads us to accept fixed effects.

5.4. Productivity spillover

Result 4. *The inter-sectoral linkages shorten the economic distances among sectors and are an important channel through which growth in a sector can boost aggregate economic growth in the rest of an economy.*

Inter-sectoral spillover arises from changes in the independent variables that result in benefits accruing to other sectors. Above-mentioned subsections indicate that the coefficients in Column 6 of Table 2, "sectoral and time fixed effects bias-corrected",

are most consistent and should be used to analyze the pivotal role played by inter-sectoral linkages. The inter-sectoral lagged dependent variable $\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$ is positive and significant (0.09), which implies the presence of inter-sectoral dependence: labor productivity in a sector is associated with labor productivity in related sectors. As stated in Section 2.1., the productivity-enhancing effects taking place through inter-sectoral linkages may come from cheaper inputs, more funds, external knowledge, new economic norms, or higher labor quality. Our findings are broadly consistent with Paz's (2012) result that inter-sectoral productivity spillover accounts for 70% of the increase in productivity. Our findings are also in line with the result from Moretti (2004) that productivity spillover is stronger across plants that are 'close' in both the geographic and the technological senses. Another example is a study by the European Commission (2007), in which the strongest inter-sectoral linkages are displayed in energy, food and textiles.

Y-axis of Fig. 1 is the coefficients on productivity spillover from other sectors $\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$ to each sector, which is listed in Column 3 of Table 3. The x-axis is the rank in value of economic distance, which is measured by a sensitivity-of-dispersion index. This index measures the increase in the production of sector s, driven by a unit increase in the final demand for all sectors in the national economic system, and can be interpreted as a measure of *forward linkage*. The higher the power of dispersion, the smaller is the rank and distance. A linear fitted line is superimposed. The slope (standard error) of the fitted line is -0.01 (0.00), R^2 is 0.36. Fig. 1 shows that productivity spillover and economic distance move in opposite directions. This finding is supported by, among others, Moretti (2004) and Greenstone et al. (2010).

5.5. Infrastructure spillover

Result 5. *Spillover effect of infrastructure, which is omitted in the non-spatial panel regression, takes place through intersectoral linkages.*

The direct impact includes the feedback effects that arise as a result of impacts passing through related sectors, and back to the typical sector itself. Since the elasticity of infrastructure per region $\ln(G/L_{region})$ in the non-inter-sectoral model (reported in Column 4 of Table 2) is 0.16, the elasticity of $\ln(G/L_{region})$ (reported in Column 6 of Table 2) is 0.11, and the direct effect of $\ln(G/L_{region})$ (reported in Column 1 of Table 4) is 0.10, the feedback of $\ln(G/L_{region})$ is -0.01, and the elasticity of $\ln(G/L_{region})$ in the non-inter-sectoral model is overestimated by 0.06 or 60% of the direct effect. Given that infrastructure generates direct impact, it is reassuring to see that at the margin infrastructure fosters economic growth.

The indirect impact captures the influence among sectors which do not directly conflate with each other. The indirect impact of infrastructure per region $\ln(G/L_{region})$ reported in Column 2 of Table 4 is 0.09, which is very close to its direct impact 0.10. The ratio of the indirect effect to the direct effect in the inter-sectoral Durbin model is 90% for $\ln(G/L_{region})$. If infrastructure per region shared by one sector changes, the result is a change in not only the productivity of this sector, but also productivity in related sectors. The ratio of the productivity change in its related sectors to the productivity change in the sector itself is 1 to 1.1 in the
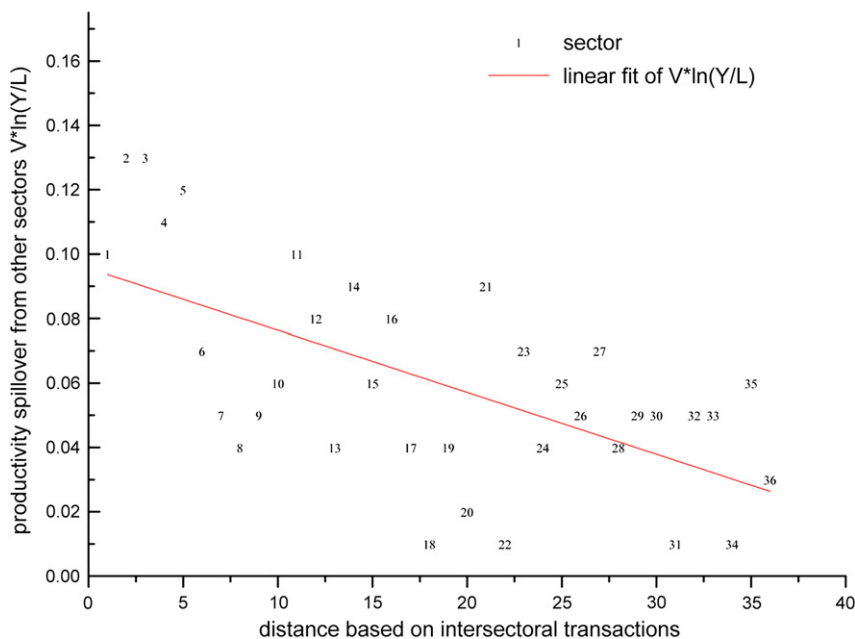

Fig. 1. The spillover of productivity in Chinese sectors by distance.

Table 3
The spillover of productivity in Chinese sectors by distance.

Sector	Distance rank	$\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$
Medicines	1	0.10[c]
Smelting and pressing of ferrous metals	2	0.13[c]
Artwork and supply of electric and heat power	3	0.13[c]
Textile	4	0.11[a]
Non-metallic mineral products	5	0.12
Extraction of petroleum and natural gas	6	0.07[c]
Smelting and pressing of non-ferrous metals	7	0.05
Communication equipment, computers	8	0.04
General purpose machinery	9	0.05[c]
Petroleum, coking, processing of nuclear fuel	10	0.06
Mining and washing of coal	11	0.10
Paper and paper products	12	0.08[c]
Metal products	13	0.04[c]
Measuring and cultural instruments	14	0.09[c]
Transport equipment	15	0.06
Electrical machinery	16	0.08
Rubber	17	0.04[a]
Mining and processing of non-ferrous metal ores	18	0.01
Special purpose machinery	19	0.04
Leather, fur, feather and related products	20	0.02
Timber, manufacture of wood, bamboo	21	0.09[c]
Processing of food from agricultural products	22	0.01
Mining and processing of ferrous metal ores	23	0.07[c]
Mining and processing of nonmetal ores	24	0.04
Plastics	25	0.06[c]
Furniture	26	0.05
Printing, reproduction of recording media	27	0.07[b]
Textile wearing apparel, footwear and caps	28	0.04[c]
Chemical fibers	29	0.05
Food	30	0.05
Production and supply of water	31	0.01
Raw chemical material and chemical products	32	0.05[c]
Tobacco	33	0.05
Beverages	34	0.01[c]
Production and supply of gas	35	0.06[c]
Articles for culture, education and sport	36	0.03[c]

[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

case of $\ln(G/L_{region})$. The change in related sectors moves in the same direction. To the degree that sectoral transactions are nationally mobile and connected, infrastructure shared by one sector, through its effects on production cost and business environment, may have important impacts on resource allocation and economic growth in other sectors. This sectoral multiplier effect usually happens during the process of industrialization (Park, 1989). Due to the existence of linkages, key sectors lead the national economy as a whole (Hirschman, 1958). Here we complement Eberts and McMillen's (1999) finding that one of the external sources of productivity is infrastructure.

The infrastructure shared by other sectors $\sum_{m=1}^{S} V_{sm} \ln(G/L_{region})_{mti}$ in Column 6 of Table 2 is 0.05 and significant. It is possible that sector s in one region is less developed than its related sectors in other regions where local governmental investment on

Table 4
Direct impact VS indirect impact of intersectoral model (Eq. (6)).

Explanatory variables	Sectoral and time fixed effects bias-corrected		
	Direct effect (1)	Indirect effect (2)	Total effect (3)
$\ln(K/L)$	0.51[a]	−0.01[a]	0.50[a]
	(41.85)	(3.93)	(25.73)
$\ln(G/L_{region})$	0.10[a]	0.09[a]	0.19[a]
	(7.17)	(7.56)	(14.85)
$\ln C$	0.02[c]	0.02[a]	0.04[a]
	(1.67)	(2.89)	(3.17)

[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

technological infrastructure facilitates technology development and linkages (Dahlman, 2007). As sector s employs intermediate goods in the process of production of the final goods from its related sectors, technological progress can be transferred from its related sectors and economic ties become more important than geographic ties. This result is somewhat in line with an earlier theory by Dembour & Wauthy (2009) that spatial externalities and the public nature of infrastructure make the firms less sensitive to their physical location.

To conclude, the contribution of inter-sectoral spillover stems not only from its direct impact of capital and infrastructure, but more importantly from extensive indirect effects of infrastructure on various sectors.

5.6. Sectoral agglomeration

Result 6. *The contribution of sectoral agglomeration to productivity is low. This might be because of agglomeration diseconomies, which can be reduced partially by positive infrastructure spillover among sectors.*

Since the elasticity of sectoral agglomeration C in the non-inter-sectoral model (reported in Column 4 of Table 2) is 0.03, the elasticity of sectoral agglomeration C in the two-way fixed effects inter-sectoral Durbin model (reported in Column 6 of Table 2) is 0.01, and the direct effect of agglomeration (reported in Column 1 of Table 4) *is* 0.02, the feedback effect of lnC is −0.01, and the overestimated elasticity of lnC in the non-inter-sectoral model is 0.01 or 50% of the direct effect. These results indicate that the inter-sectoral Durbin model is able to add some interesting insights on the patterns of productivity growth across sectors. Our finding is supported by the result in Martinez et al. (2007) that doubling employment density raises average labor productivity in the industrial sector by between 3 and 5%.

In Column 2 of Table 4, the indirect impact of sectoral agglomeration lnC is 0.02. The ratio of the indirect effect to the direct effect in the inter-sectoral Durbin model is 100% for lnC. If the agglomeration degree of one sector changes, the result is a change in not only the sectoral productivity of this sector, but also the sectoral productivity in the related sectors. The ratio of the productivity change in its neighboring areas to the productivity change in the region itself is 1 to 1 in the case of lnC. Theoretically, the indirect effect should be smaller than the direct effect. However, other scholars have also found the indirect impact surpasses the direct impact. In Lesage (2008), the indirect impact of population density (0.1021) is larger than its direct impact (0.0031), and the indirect impact of in-migration (0.2319) is larger than its direct impact (0.1331). In Pijnenburg and Kholodilin (2011), the indirect impact of physical capital (0.31) is larger than its direct impact (0.13).

Considering the statistically significant and negative coefficient of $\sum_{m=1}^{S} V_{sm} \ln C_{mti}$ in Column 6 of Table 2, it is reasonable to assume that infrastructure and knowledge spillover offset agglomeration diseconomies through inter-sectoral linkages, as shown in Fig. 2. Agglomeration diseconomies such as congestion, pollution and over-competition increase cost, reduce market opportunities and deter investment. Due to these negative effects, locational proximity becomes less important than economic cooperation among sectors. An increasing body of literature in sectoral agglomeration suggests that linked sectors do not totally relocate from one location to another (e.g., Kranich, 2011). The negative effects of agglomeration is offset by positive effect and infrastructure spillover. For example, investments in wastewater infrastructure can reduce pollution; infrastructure investment on transportation sectors can reduce cost associated with congestion and make transportation networks greener; infrastructure investment on ICT sectors allows firms to access to foreign market, thus relieving competition in the domestic market.

5.7. Other

The inter-sectoral lagged independent variable $\sum_{m=1}^{S} V_{sm} \ln(K/L)_{mti}$ in Column 6 of Table 2 is negative and insignificant (−0.01). In some previous studies (e.g. Elhorst & Zigova, 2011), a negative and insignificant lagged independent variable is interpreted as lack of cross-fertilization effects across nearby units.
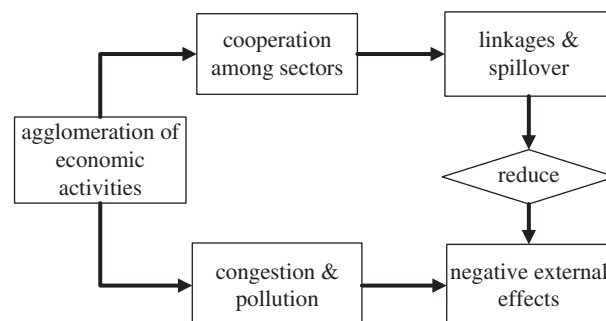

Fig. 2. Agglomeration and linkages.

The indirect impact of $\ln(K/L)$ reported in Column 2 of Table 4 is -0.01 and not statistically different from 0. The result is consistent with the studies of Lesage & Fischer (2008), who found the indirect impact of physical capital on the income level of a typical region is -0.02, that the indirect impact of income is -0.3774 and that a 1% increase in the initial level of income of all other regions would decrease the income level of a typical region by 0.37%.

6. Estimates of spatial distance

For comparison with inter-sectoral models, spatial models are estimated in this section. The 1st–4th columns of Table 5 disclose whether non-spatial panel data models are better than spatial models. The results in Column 2 (LR test: 3021.21, with 31 degrees of freedom, p<0.01) indicate that the null hypothesis that the spatial fixed effects are jointly insignificant must be rejected. The null hypothesis that the time fixed effects are jointly insignificant must be rejected (LR 1469.33, with 432 degrees of freedom, p<0.01). In a word, non-spatial models must be rejected.

Columns 5, 6, and 7 of Table 5 help us to select the best model among the spatial Durbin model, the spatial lag model and the spatial error model, and to choose between random effects and fixed effects. Column 5 gives the results when using the direct approach, which yields an inconsistent parameter. Wald-lag, LM-lag, Wald-error and LM-error results indicate that both the spatial error model (SEM) and the spatial lag model (SLM) must be rejected in favor of the spatial Durbin model.

Some cases using spatial methods find the Durbin model is not always dominant over a lag model and an error model. Kalenkoski and Lacombe (2011) created a model which incorporates SDM, SLM and SEM, and used the LR test to prove that SDM can be simplified to SLM in the analysis of minimum wages and teen employment. Glass, Kenjegalieva, and Sickles (2012) pointed out that SEM better captures spatial dependence than SDM and SLM with regard to disaggregated data.

Column 6 gives unbiased coefficients when controlling for unobserved time-invariant spatial heterogeneity. Column 7 reports the results when μ_i is treated as a random variable rather than as a set of fixed effects. The *Hausman* test result and φ value in Column 7 imply that random effects are rejected in favor of fixed effects. Therefore, we should only adopt the coefficients in Column 6.

In Column 2 of Table 6, the indirect effect of infrastructure is negative. This might be because that infrastructure makes a region more attractive to firms than other regions, exerting negative influence on other regions. This result contrasts somewhat

Table 5
Conventional model, spatial lag model, spatial error model and spatial Durbin model.

Eq. (9): dependent variable: industrial output per worker $\ln(Y/L)_{its}$							
	Without spatial interaction effects				With spatial interaction effects		
	Pooled OLS (1)	SPATIAL fixed effects (2)	Time fixed effects (3)	Spatial and time fixed effects (4)	Spatial and time fixed effects (5)	Spatial and time fixed effects bias-corrected (6)	Random spatial effects, fixed time effects (7)
Intercept	1.06[a]						
$\ln(K/L)_{its}$	0.57[a]	0.51[a]	0.68[a]	0.58[a]	0.57[a] (69.47)	0.57[a] (68.32)	0.57[a] (69.44)
$\ln(G/L_{region})_{its}$	0.20[a]	0.29[a]	0.18[a]	0.27[a]	0.25[a] (31.80)	0.25[a] (31.36)	0.25[a] (31.86)
$\ln C_{its}$	0.02[a]	-0.01[b]	0.02[b]	0.03[a]	0.03[a] (3.43)	0.03[a] (3.39)	0.0298[a] (3.41)
$W_{ij}\ln(Y/L)_{jts}$					0.23[a] (-3.56)	0.02[c] (1.75)	-0.04[a] (-3.25)
$W_{ij}\ln(K/L)_{jts}$					-0.01 (-0.65)	-0.02[a] (-2.60)	-0.01 (-0.80)
$W_{ij}\ln(G/L_{region})_{jts}$					-0.05[a] (-3.53)	-0.07[a] (-4.53)	-0.06[a] (-3.80)
$W_{ij}\ln C_{jts}$					0.00 (0.15)	0.00 (0.05)	0.00 (0.13)
φ							0.06[a]
σ^2	1.64	0.89	1.36	0.63	0.82	0.85	0.83
R^2	0.33	0.30	0.36	0.34	0.67	0.67	0.62
$Corr^2$					0.36	0.36	0.37
LM-lag	97.57[a]	358.29[a]	0.88[a]	6.57[a]	14.57[a]	14.57[a]	
rob. LM-lag	331.63[a]	650.19[a]	9.83[a]	7.31[a]			
Wald-lag					13.33[a]	29.52[a]	15.69[a]
LM-error	45.93[a]	40.12[a]	13.56[a]	1.29[a]	28.84[a]	28.84[a]	
rob. LM-error	280.00[a]	332.02[a]	22.51[a]	2.03[a]			
Wald-error					28.60[a]	25.98[a]	31.03[a]
Hausman							667.04[a]
LR		3021.21[a]	1469.33[a]				

[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

Table 6
Direct impact VS indirect impact of spatial model.

Explanatory variables	Spatial and time fixed effects bias-corrected		
	Direct effect (1)	Indirect effect (2)	Total effect (3)
$\ln(K/L)$	0.57[a] (66.52)	−0.02[b] (2.04)	0.55[a] (28.26)
$\ln(G/L_{\text{region}})$	0.25[a] (31.41)	−0.06[a] (−4.22)	0.18[a] (10.79)
$\ln C$	0.02[a] (3.39)	0.00 (0.05)	0.03[c] (1.53)

[a] Significant at 1%.
[b] Significant at 5%.
[c] Significant at 10%.

with an earlier theory by Dembour and Wauthy (2009) that spatial externalities and the public nature of infrastructure make the firms less sensitive to the physical location.

The coefficient of spatial distance $\sum_{j=1}^{N} W_{ij} \ln(Y/L)_{jts}$ is 0.02 in Table 5, while the coefficient of intersectoral distance $\sum_{m=1}^{S} V_{sm} \ln(Y/L)_{mti}$ is 0.09 in Table 2. Our results confirm the result by Moretti (2004) that spillover among sectors that are economically close is larger than spillover among sectors that are economically distant.

7. Conclusion

This paper adopts a novel method to explore how key sectors can fuel productivity growth in other sectors through inter-sectoral spillover. Specifically, economic distance, which is represented by supplier and customer linkages, is integrated with a spatial Durbin model in measuring productivity spillover. The inter-sectoral spillover is further dissected into the indirect effect which captures interdependencies among sectors, and the direct effect which encompasses the feedback effects from other sectors to a typical sector (Table 4). The model departs from the literature because spatial econometric models mainly consider geographic concentration of sectors, and omit links between geographically distant but economically close sectors.

Our major findings can be briefly summarized as follows. First, the productivity for any sector is not only determined by production factors (such as capital) in that sector, but also is conditional on other linked sectors. With product as a carrier of innovation, the input–output dependencies transfer knowledge among sectors, so that sectors can accelerate and deepen their innovation process. Along with *knowledge spillover*, factor demand linkages among sectors are likely to amplify the effect of *cost reduction*, *pecuniary externalities*, *the standardization of rules*, *and the improvement of labor quality*. Economic distance is negatively correlated with productivity spillover, and is more important than spatial distance in transmitting productivity spillover. As an attempt to make use of productivity spillover among sectors, many countries have adopted the policy of pushing forward the development of pillar sectors, such as mining, energy and ICT. Our findings shed light on the puzzle of whether productivity spillover varies as a function of economic distance (see evidence in Greenstone et al., 2010). Our result also sheds light on why supplier and customer linkages are the strong Marshallian forces (see evidence in Ellison et al., 2010).

Second, investment in public capital generates strong and positive spillover effects on both the level of per capita income and growth rates. Infrastructure promotes sectoral factor mobility, leads to specialization and enlarges production possibility frontiers. Infrastructure such as the information highway and transportation increases the connections among sectors. In turn, with linkages, the policy of investing limited public capital in key sectors promotes the development of related sectors and improves systemic competitiveness.

Third, the sectoral agglomeration degree exhibits low output elasticity. This is best explained in terms of agglomeration diseconomies. Local competition fosters the rapid adoption of technologies and the economic scale of a firm's geographical location enhances its productivity. However, the magnitude of the productivity spillover depends weakly on the geographic proximity of sectors. Besides, there exist sectoral agglomeration diseconomies, which can be partly offset by the benefit brought by linkages and infrastructure.

Appendix A. Sectoral matrix

This approach is supported by Greenstone et al. (2010) who prove that transactions among industries can represent economic distance and agglomeration spillovers. The calculation can be expressed:

$$V_{ij} = \frac{\frac{d_{ij}}{\sum_i d_{ij}} + \frac{d_{ij}}{\sum_j d_{ij}}}{2}, \qquad \sum_i d_{ij} \neq 0, \sum_j d_{ij} \neq 0$$

i is the row index, j is the column index. d_{ij} is an element of the transaction matrix, $\sum_i d_{ij}$ is the column sum of intermediate demand and the input that sector i uses from other sectors in its production process. $\sum_j d_{ij}^i$ is the row sum of intermediate demand and the material sector i provides to other sectors. The matrix V_{ij} is the economic distance matrix and represents how each sector is woven into the structure of the economy. The exercise that is most closely related to ours is European Commission (2007), which uses a similar method to measure the relationship between sectors. But the European Commission (2007) ignores intermediate transactions that score below 10%.

The steps are as follows:

Step 1. Categorize intermediate producers into S industries according to the 'Chinese Statistic Yearbook' and 'National Economic Industrial Classification'.
Step 2. Make an $S \times S$ matrix V, (in the paper, $S = 36$). The columns in the matrix reveal the quantity of product each industry buys from other sectors.
Step 3. Divide sector's shares of intermediate uses by the sector's total intermediate outputs to obtain $\frac{d_{ij}}{\sum_i d_{ij}}$. For instance, 13.62% of total intermediate inputs of the Textile industry come from Rubber products (backward linkages effect).
Step 4. Divide sector's shares of intermediate uses by the sector's total intermediate inputs to obtain $\frac{d_{ij}}{\sum_j d_{ij}}$. For instance, 50.64% of total intermediate outputs of the Rubber industry are delivered to the Textile industry (forward linkages effect)
Step 5. Average the two figures obtained from step 3 and step 4. In this case, the flow index is 32.13%

One could object to our methodology by arguing that a transaction matrix cannot replace a spatial matrix. Yet, such a criticism is not valid. First, there is no endogeneity problem. We do not use the transaction matrix in the current year to make the economic matrix. The inter-sectoral transaction matrices are refined based on data for *three periods*, each period covering 3 to 5 years, so that each element of the matrices is not determined by any variables in a particular year.

Second, a transaction matrix is able to encapsulate as much information as a spatial matrix, such as 'economic distances' and economic proximity. A spatial matrix depicts the proximity and geographic distribution of spatial units. Its values disclose pair-wise distances of the observations to each other. Similarly, the inter-sectoral transaction table describes sectoral interactions where labor, capital, goods or services are readily moveable among sectors. Its values represent the interaction of sectors with other sectors. The larger the value a sector has, the more of its products are purchased by other sectors, and the larger is the mutual influence between it and other sectors.

Third, neighboring relationships should be extended from geographic neighbors to economic neighbors. Technology and material flows contained in sectoral interactions provide the very foundation of commodity market equilibria. Sectoral interaction brings about economic spillovers and innovation diffusion (Park, 2004; Malerba, Mancusi, & Montobbio, 2007). Ignoring sectoral linkages means ignoring one of the main sources of productivity growth.

Appendix B. 31 provinces in China

Table 7. 31 provinces in China.

No	Province
1	Beijing
2	Tianjin
3	Hebei
4	Shanxi
5	Inner Mongolia
6	Liaoning
7	Jilin
8	Heilongjiang
9	Shanghai
10	Jiangsu
11	Zhejiang

(*continued*)

No	Province
12	Anhui
13	Fujian
14	Jiangxi
15	Shandong
16	Henan
17	Hubei
18	Hunan
19	Guangdong
20	Guangxi
21	Hainan
22	Chongqing
23	Sichuan
24	Guizhou
25	Yunnan
26	Tibet
27	Shaanxi
28	Gansu
29	Qinghai
30	Ningxia
31	Xinjiang

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