Industry-Specific Productivity and Spatial Spillovers through input-output linkages: evidence from Asia-Pacific Value Chain[1]

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Abstract

This paper develops a theoretical growth model which combines spatial spillovers and productivity growth heterogeneity at the industry-level. We exploit the global value chain (GVC) linkages from inter-country input-output tables to describe the spatial interdependencies in technology. The spillover effects from factor inputs and Hicks-neutral technical change are separately identified in the model and decomposed into domestic and international effects respectively. Country-specific production functions are estimated using a spatial econometric specification for the industries of the sample. Most of the spillover effects of factor inputs, which we measure in terms of external factor elasticities, are found to be statistically and economically significant. The spillover effects of technical change offered and received vary widely across industries and contain information about the technological diffusion in GVC. Most prominently, the spillover of productivity growth offered by US Electrical and Optical Equipment is 5.05%, which is the highest of all industries in our sample. Chinese Electrical and Optical Equipment absorbs the spillover of productivity growth of 1.04% annually, with the international component a relatively low 0.12%, which is substantially smaller than Korea's absorption of international spillovers that add 0.53% annually to this key industry.

Keywords: Industry-specific productivity, spatial panel model, technological spillovers, global value chain

JEL classification codes: C23, C51, C67, D24, O47, R15

1 Introduction

Over the past two decades the world economy has evolved rapidly and the network structure of the global specialization has been dramatically transformed. The growth and structure of individual national economies appear to depend critically on the growth rates of other countries. Through the increasingly enhanced linkages of the production network, a shock in one country can trigger misallocations of resources in other countries. However, the way in which and the extent to which this complex and sophisticated network of domestic and cross-border production-sharing activities impacts national growth largely has been missing in the empirical economic growth literature.

Global value chains (GVCs) are the most important drivers of globalization (World Bank et al., 2017). Currently nearly 70% of world trade in goods is composed of intermediate inputs such as raw materials and capital components that are used to produce finished products.[2]. The linkages among major economies in the Asia-Pacific area, which along with the US are the foci of our empirical analyses, measured by value added exports based on the work of Johnson and Noguera (2012) are presented in Figure1[3]. The share of domestic linkages has declined for all the five countries from 1995 to 2010, the period we study, while foreign value added occupies an increasingly larger share. The linkages between those countries and China from both the input and output directions has expanded, implying significant changes in the pattern of the use of labor services. Koopman et al. (2012, 2014) develop a detailed accounting framework to trace the value-added flow based on a vertical specialization model and use the World Input-Output tables to estimate domestic and foreign components in export. Acemoglu et

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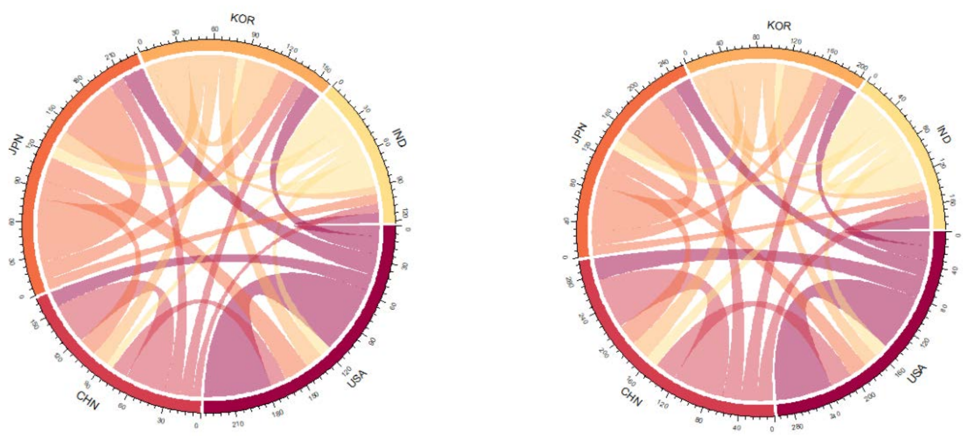
[2] The UNSD Commodity Trade (UN Comtrade) database

[3] Instead of the conventional measurement of trade by gross value of goods that may cause the "double-counting" problem, we use Trade in Value added to construct the graph.

al. (2016) tested the propagation mechanism of TFP shocks through the input-output network at the industry level. Carvalho and Tahbaz-Salehi (2019) present the theoretical foundations for the role of input-output linkages as a channel for shock propagations. Timmer et al. (2015, 2017) summarized the effect that the global value chain has on the productivity of industries through these input-output linkages. Understanding how industries in different economies link, specialize, and grow can help shed light on why some lower-income countries are catching up to high-income countries, while some are not, during the rapid development in global value chains (GVCs).



(a) Trade in Value added in 1995 (b) Trade in Value added in 2010

FIGURE 1

Value-added trade linkages between US, China, Japan, Korea and India

Notes: the width of the strip represent the domestic or foreign value added in forth root.

The impact of globalization on the national economy has been widely explored in international and growth economics. Different from the assumptions in traditional neoclassical growth theory that the economies are independent and non-interactive, the growing literatures recognize that technological advances diffuse and are transmittable across economies. This technological spillover has been found to be a major engine for economic growth (Ertur and Koch, 2007).

Technological spillovers have been the focus of a number of studies of economic growth resulting from international trade (Coe and Helpman, 1995; Eaton and Kortum, 1996), foreign direct investment (Caves, 1996) and geographical proximity (Keller, 2002). Several studies have also estimated growth models using spatial econometric techniques. Ertur and Koch (2007) proposed a spatial version of the Solow (1956, 1957) neoclassical growth mode and found significant spatial effects on economic growth. Fingleton and López-Bazo (2006) found strong empirical support for the existence of externalities across economies. Fingleton (2008) used spatial econometric techniques to test between the standard neoclassical growth model and the new models of economic geography. Arbia et al. (2010) suggest that geo-institutional proximity outperforms pure geographical metrics in accounting for spatial interdependence. Ho et al. (2013) extend the Solow growth model using a spatial autoregressive specification, which they use to examine the international spillovers of economic growth through bilateral trade.

However, much of the research on international spillovers is focused on national economies and implicitly assumes homogeneity in productivity growth among different nations or sectors within nations, depending on the cross-sectional -unit of observation. To investigate how interdependencies in the GVCs networks impact economic growth, and to also determine how crucial it is for world economic growth that such GVC's are not disrupted by the current political climate in the US, an investigation into industry level linkages is necessary. This is due in part to the fact that labor services and coordination in GVCs are facilitated by upstream-downstream these sectoral linkages. And as discussed in Durlauf (2000, 2001) and Brock and Durlauf (2001), the assumption of homogenous parameters in modeling economic growth across countries also may be incorrect. Canova (2004), Desdoigts (1999) and Durlauf et al. (2001) find evidence of parameter heterogeneity using different statistical methodologies. However, a proliferation of free parameters in empirical modeling also may not allow one to explain the structural factors and economic conditions behind the long-run growth phenomenon (Durlauf and Quah, 1999, Ertur and Koch, 2007). Heterogeneity in productivity growth among industries should be considered as such heterogeneity is intrinsic due to techno-economical features of each distinct sector. Jorgenson et al. (2012) note the influential power of some key industries and reveal the predominate role of IT-producing and IT-using industries as sources of productivity growth. This industry perspective on productivity and spillovers is particularly valuable as it provides intuitive information for the policy design of selecting preferential industries and bridging the development gap through encouraging the interaction in GVCs in order to promote technological advances.

A major contribution of this paper is to propose a new model for measuring the industry-specific productivity and spillovers based on a spatial production function which allows the productivity growth varies over the industries. We consider a neoclassical output per worker growth model (Solow, 1956, 1957) as augmented, for example, by Ertur and Koch (2007) to include spatial externalities in knowledge. Instead of using geographical distance to construct the spatial weights matrix, we extract the input and output flows based on the World Input-Output tables to measure economic distance between industries within/across national economies. In so doing we are able to lift the assumption of identical technical progress in all cross-sections by allowing for an industry-specific function of time based on the estimation technique developed by Cornwell et al. (1990) and Han and Sickles (2019).

We also provide more explicit insights on the spatial spillovers process in our empirical analysis using a flexible spatial production function. The direct, indirect and total marginal effects of the input factors and time trends are calculated to describe the role of spillovers from input factors as well as how technical changes are distributed within the GVCs network using both spatial autoregressive (SAR) and spatial Durbin (SDM) production functions. We follow Glass et al. (2015) who estimate these effects based on spatial translog production functions but calculate the industry-specific productivity growth spillovers by distinguishing between knowledge receiving and offering, which represent the two distinct directions of knowledge diffusion. Furthermore, in our global value chain settings, we use local Ghosh matrices to identify the portion of indirect effects that are transmitted within a country as well as the indirect effects that are transferred across the borders respectively. Through our decomposition method, we are able to distinguish between domestic and international spillovers.

This paper is organized as follows. In section 2 we set out the spatial production model with heterogeneity in technical progress using SAR and SDM specifications, and then explain our approach to measure the spatial spillovers of the inputs and Hicks-neutral technical change. We also provide the methodology to decompose the domestic and international spillovers using the local Ghosh matrices. Section 3 discusses our estimation strategy. Section 4 presents the industry-level data of the countries we study and the World Input-Output tables we used to construct the spatial weight matrix. In section 5 we estimate the production function using our methodology and discuss the productivity spillovers through Asia-Pacific value chain. Section 6 concludes.

2 Model

2.1 A production function with heterogeneity in technical progress

Consider an aggregate Cobb–Douglas production function with Hicks-neutral technical change for industry i at time t exhibiting constant returns to scale in labor, capital and intermediate input:

$$Y_i(t) = A_i(t)K_i(t)^{\alpha}M_i(t)^{\beta}L_i(t)^{\gamma}, \quad i = 1, \cdots, N, \quad t = 1, \cdots, T, \qquad (1)$$

where $Y_i(t)$ is the total output, $K_i(t)$, $M_i(t)$ and $L_i(t)$ are the capital, labor and intermediate input respectively and $\alpha + \beta + \gamma = 1$. $A_i(t)$ is the aggregate level of technology, which differs among industries and time periods.

The technology $A_i(t)$ can be described in the following form:

$$A_i(t) = \Omega_i(\mathrm{t}) = \Omega(0)_i e^{R(t)'\delta_i} \tag{2}$$

where $R(t)$ is an $L \times 1$ time-varying component that globally affects all industries, and δ_i is an $L \times 1$ the coefficients that depend on i. $\Omega_i(0)$ is the individual initial technology state. We extend the Solow model (Solow, 1956; Swan, 1956; Ertur and Koch, 2007) of identical technical progress in all industries by allowing for an industry-specific time trend. We can then write the non-spatial production function per worker as:

$$y_i(t) = A_i(t) k_i(t)^{\alpha} m_i(t)^{\beta} = \Omega_i(0) e^{R(t)'\delta_i} k_i(t)^{\alpha} m_i(t)^{\beta} \tag{3}$$

where $y_i(t) = Y_i(t)/L_i(t)$, $k_i(t) = K_i(t)/L_i(t)$, $m_i(t) = M_i(t)/L_i(t)$.

Decomposing $R(t)'\delta_i$ into a global time trend $R(t)'\delta_g$ and an industry-specific term $R(t)'u_i$ and then taking the logarithm of Eq. (3), we have the following linear regression model in the form of Cornwell et al. (1990)[4]:

$$\ln y_{it} = \ln k_{it}\alpha + \ln m_{it}\beta + \ln\Omega_i(0) + R_t{}'\delta_g + R_t{}'u_i + v_{it} \tag{4}$$

where u_i are assumed to be *iid* zero mean random variables with covariance matrix Δ, and v_{it} is the usual disturbance term assumed to a random noise following *iid* N(0, σ_v^2). This model assumes the heterogeneous initial state and progress of technology. However, we note that if there are no heterogeneities, i.e., $\Omega_i(0)$ and u_i are constant, then the production function can be written in the usual form and the Eq. (4) reduces to the standard panel data model with a time trend.

[4] In a series of papers Park, Sickles, and Simar (1998, 2003, 2007) showed, among other things, that the time varying CSS and time invariant Schmidt and Sickles (1984) panel data estimators for the stochastic panel frontier were semiparametric efficient for the slope coefficients in the class of linear panel data models with correlated random effects. See also Sickles and Zelenuyk (2019) for a more extensive discussion of these and many other estimators for average and frontier production models.

2.2 Spatial model with technology spillover

To account for the technology spillover through the linkage of industries, the effect of cross-sectional dependence should be considered in the production functions. Ertur and Koch (2009) modeled the technology as a function of a common global time trend, per worker capital and a spatial lag of a country's neighbor's technology. Here we relax the assumption of Hicks-neutral technical change by allowing each industry i to have industry-specific technical progress $\Omega_i(\mathrm{t})$ while at the same time allowing the industry to absorb knowledge diffusion from its neighbors. We assume that knowledge diffusion is influenced by the strength of linkage w_{ij} with neighbor-industry j and neighbor-industry j's labor productivity $y_j(t)$. The Solow residual then can be written as

$$A_i(\mathrm{t}) = \Omega_i(\mathrm{t}) \prod_{j\neq i}^{N} y_j(t)^{\rho w_{ij}} = \Omega_i(0) e^{R(t)'\delta_i} \prod_{j\neq i}^{N} y_j(t)^{\rho w_{ij}}, \tag{5}$$

And this leads to the following production function per worker:

$$y_i(t) = \Omega_i(0) e^{R(t)'\delta_i} \prod_{j\neq i}^{N} y_j(t)^{\rho w_{ij}}\, k_i(t)^{\alpha} m_i(t)^{\beta}. \tag{6}$$

Taking the logarithms of the expression, we obtain a Spatial Autoregressive form regression model as follows:

$$\ln y_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln y_{jt} + \ln k_{it}\alpha + \ln m_{it}\beta + \ln \Omega_{i0} + R_t{}'\delta_g + R_t{}'u_i + v_{it}, \tag{7}$$

which we rewrite in matrix form as

$$y = \rho(W_N \otimes I_T) y + k\alpha + m\beta + \omega_0 + r\delta_g + qU + V, \tag{8}$$

where y, k, m and V are $NT \times 1$ vectors, $\omega_0 = \Omega_{i0} \otimes \iota_T$, ι_T is T dimensional vector of ones, $r = \iota_N \otimes R$, ι_N is N dimensional vector of ones, $R = (R_1, R_2, \cdots, R_T)'$, $q = \iota_N \otimes diag(R)$, is $NT \times LN$ matrix, δ_g is $L \times 1$ vector, and U is a $LN \times 1$ vector.

In a more general case, we can assume technical spillovers are not just influenced by the neighbor's labor productivity, but by the neighbor's technology $A_i(t)$, input levels of per-worker physical capital $k_j(t)$, and per-worker intermediate input $m_j(t)$. We also can consider the spatial linkages that may have effects on an industry's output when its neighbor changes its input. This leads to the following expression for technology:

$$A_i(\mathrm{t}) = \Omega_i(\mathrm{t}) \prod_{j\neq i}^{N} A_j(t)^{\rho w_{ij}} \prod_{j\neq i}^{N} k_j(t)^{\phi w_{ij}} \prod_{j\neq i}^{N} m_j(t)^{\varphi w_{ij}}$$

$$= \Omega_i(\mathrm{t}) \prod_{j\neq i}^{N} \left[y_j(t)/k_j(t)^{\alpha} m_j(t)^{\beta}\right]^{\rho w_{ij}} \prod_{j\neq i}^{N} k_j(t)^{\phi w_{ij}} \prod_{j\neq i}^{N} m_j(t)^{\varphi w_{ij}}$$

$$= \Omega_i(0) e^{R(t)'\delta_i} \prod_{j\neq i}^{N} y_j(t)^{\rho w_{ij}} \prod_{j\neq i}^{N} k_j(t)^{(\phi-\alpha\rho) w_{ij}} \prod_{j\neq i}^{N} m_j(t)^{(\varphi-\beta\rho) w_{ij}}. \qquad (9)$$

Replacing this expression in the production function, then take logarithms, we obtain the production function in a Spatial Durbin form[5]:

$$\ln y_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln y_{jt} + \ln k_{it}\alpha + \ln m_{it}\beta + \ln\Omega_{i0} + R_t{}'\delta_g + R_t{}'u_i + v_{it}$$
$$+ \sum_{j=1}^{N} w_{ij} \ln k_{jt}\,(\phi - \rho\alpha) + \sum_{j=1}^{N} w_{ij} \ln m_{jt}\,(\varphi - \rho\beta). \qquad (10)$$

Likewise, the matrix form of (10) is given by

$$y = \rho(W_N \otimes I_T) y + k\alpha + m\beta + \omega_0 + r\delta_g + qU + V$$
$$+(\phi - \rho\alpha)(W_N \otimes I_T)k + (\varphi - \rho\beta)(W_N \otimes I_T)m. \qquad (11)$$

2.3 Technology Spillovers and Spatial Elasticities

As demonstrated in LeSage and Pace (2009), for spatial models the usual interpretation of α and β as elasticities of input factors is not valid. They instead suggest the following approach to calculate direct, indirect, and total marginal effects. First resolve the linear system for y, if $\rho \neq 0$ and if $1/\rho$ is not an eigenvalue of $W_N \otimes I_T$, and rewrite Eq. (8) and (11) as (12) and (13):

$$y = \alpha(I - \rho W_N \otimes I_T)^{-1} k + \beta(I - \rho W_N \otimes I_T)^{-1} m$$
$$+(I - \rho W_N \otimes I_T)^{-1}\left(\omega_0 + r\delta_g + qU + V\right) \qquad (12)$$

$$y = (I - \rho W_N \otimes I_T)^{-1}[\alpha I + (\phi - \rho\alpha) W_N \otimes I_T]k + (I - \rho W_N \otimes I_T)^{-1}$$

[5] Strictly Eq.(12) is a partial spatial Durbin model, the local spatial function of Hicks-neutral technological change is omitted since the introduction of $\sum_{j=1}^{N} w_{ij} R_t{}'\delta_g$ would be perfect collinearity with $R_t{}'\delta_g$.

$$[\beta I + (\varphi - \rho\beta)W_N \otimes I_T]m + (I - \rho W_N \otimes I_T)^{-1}\left(\omega_0 + r\delta_g + qU + V\right). \quad (13)$$

Differentiating Eq. (13) with respect to per-worker capital yields the following matrix of direct and indirect effects for each industry, where the right-hand side of Eq. (14b) is independent of the time index:

$$E_k \equiv \left[\frac{\partial \ln y}{\partial \ln k_1}, \frac{\partial \ln y}{\partial \ln k_2}, \cdots, \frac{\partial \ln y}{\partial \ln k_N}\right]_t = \begin{bmatrix} \frac{\partial \ln y_1}{\partial \ln k_1} & \frac{\partial \ln y_1}{\partial \ln k_2} & \cdots & \frac{\partial \ln y_1}{\partial \ln k_N} \\ \frac{\partial \ln y_2}{\partial \ln k_1} & \frac{\partial \ln y_2}{\partial \ln k_2} & \cdots & \frac{\partial \ln y_2}{\partial \ln k_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \ln y_N}{\partial \ln k_1} & \frac{\partial \ln y_N}{\partial \ln k_2} & \cdots & \frac{\partial \ln y_N}{\partial \ln k_N} \end{bmatrix}_t \quad (14a)$$

$$= (I_N - \rho W_N)^{-1} \begin{bmatrix} \alpha & w_{12}(\phi - \rho\alpha) & \dots & w_{1N}(\phi - \rho\alpha) \\ w_{21}(\phi - \rho\alpha) & \alpha & \dots & w_{2N}(\phi - \rho\alpha) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi - \rho\alpha) & w_{N2}(\phi - \rho\alpha) & \cdots & \alpha \end{bmatrix}. \quad (14b)$$

Then the mean direct effect of per-worker capital for all the industries, which we denote e_k^{Dir}, is the average of the diagonal elements of the matrix in Eq. (14b) for the SDM model. The indirect effects of per-worker capital, which we denote e_k^{Ind}, are the average row-sum of the off-diagonal elements of the matrix in Eq. (14b). The mean total effects of per-worker capital is $e_k^{Tot} = e_k^{Dir} + e_k^{Ind}$ (LeSage and Pace, 2009). In the SAR model, the direct, indirect and total effects can also be calculated using Eq. (14b) but with the off-diagonal elements set equal to zero. Likewise, we can calculate the effects for per-worker intermediate e_m^{Dir}, e_m^{Ind} and e_m^{Tot}. Under the assumption of constant returns to scale, the effect for k and m are equivalent to the elasticities of capital and intermediate inputs. However, in the spatial model the direct elasticity also includes feedback effects when the input changes in industry i affect a neighbor industry's output, and this effect on neighbor industries rebounds and affects industry i's output via the inter-industry linkage. The indirect elasticity refers to the percentage change in industry i's output due to a percentage increase in the sum of the input across all the other $N-1$ industries. Finally, the calculation of total elasticity is based on all N industries in the sample simultaneously changing their input, not just industry i or the other $N-1$ units (Glass, et al., 2015). It can be shown that the direct elasticity of labor is $e_l^{Dir} = 1 - e_k^{Dir} - e_m^{Dir}$ and the indirect elasticity of labor is $e_l^{Ind} = -e_k^{Ind} - e_m^{Ind}$. Therefore the total elasticity of labor $e_l^{Tot} = 1 - e_k^{Tot} - e_m^{Tot}$ and constant returns to scale still holds in the spatial settings[6].

In the same way, we can describe the Hicks-neutral technical change over time and the magnitude of spillovers between the industries through spatial correlation. By differentiating Eq. (13) with respect to the time trend, this productivity change spillover can be measured by the indirect marginal effect from the spatial model:

$$g_t \equiv \left[\frac{\partial \ln y}{\partial t}\right]_t = (I_N - \rho W_N)^{-1} \begin{bmatrix} \frac{\partial R_t{}'}{\partial t}\delta_1 & 0 & \cdots & 0 \\ 0 & \frac{\partial R_t{}'}{\partial t}\delta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \frac{\partial R_t{}'}{\partial t}\delta_n \end{bmatrix}_t \tag{15a}$$

$$= \begin{bmatrix} \widetilde{w}_{11}\frac{\partial R_t{}'}{\partial t}\delta_1 & \widetilde{w}_{12}\frac{\partial R_t{}'}{\partial t}\delta_2 & \cdots & \widetilde{w}_{1n}\frac{\partial R_t{}'}{\partial t}\delta_n \\ \widetilde{w}_{21}\frac{\partial R_t{}'}{\partial t}\delta_1 & \widetilde{w}_{22}\frac{\partial R_t{}'}{\partial t}\delta_2 & \cdots & \widetilde{w}_{2n}\frac{\partial R_t{}'}{\partial t}\delta_n \\ \vdots & \vdots & \ddots & \vdots \\ \widetilde{w}_{n1}\frac{\partial R_t{}'}{\partial t}\delta_1 & \widetilde{w}_{n2}\frac{\partial R_t{}'}{\partial t}\delta_2 & \cdots & \widetilde{w}_{nn}\frac{\partial R_t{}'}{\partial t}\delta_n \end{bmatrix}_t, \tag{15b}$$

where $\widetilde{w}_{ij}$ is the element of $(I_N - \rho W_N)^{-1}$. The diagonal elements of the matrix in Eq. (15b), which we denote as $gDir_t$, is the direct effect, which represents the productivity change for industry i itself at time t. However, the indirect effect has two different interpretations depending on which directions to sum the off-diagonal elements. The row-sum of off-diagonal elements, which we denote $gInd_t^r$, represents the aggregate spillover that each industry received from all of its neighbors through the spatial linkages while the compound productivity change for industry i, measured by the summation of the direct effect and indirect effect received from all other industries, is denoted as

[6] Please see Appendix A for the derivations of the elasticities.

$gTot_t^r = gDir_t + gInd_t^r$. The column-sum of off-diagonal elements, which we denote $gInd_t^o$, represents the aggregate spillover that each industry provides its neighbors. Likewise, the compound productivity change for industry i measured by the summation of direct effect and indirect effect provided to all other industries is denoted as $gTot_t^o = gDir_t + gInd_t^o$.

2.4 Decomposition of technology spillovers by domestic and international effect

In the production system of the global value chain, knowledge spillovers not only involve industries within a country, but knowledge spillovers also cross national borders. Suppose there are two countries s and r, with Q_s and Q_r industries respectively, in a production system with a global value chain, then the spatial weight matrix W_N can be split into a block structure such as:

$$W_N \equiv \begin{bmatrix} W_{ss} & W_{sr} \\ W_{rs} & W_{rr} \end{bmatrix}, \qquad (16)$$

where W_{ss} is $Q_s \times Q_s$ matrix, W_{sr} is $Q_s \times Q_r$ matrix, W_{rs} is $Q_r \times Q_s$ matrix and W_{rr} is $Q_r \times Q_r$ matrix. W_{ss} and W_{rr} represent the linkages of the industries within the border of each country, and W_{sr} and W_{rs} represent the linkages of industries across country borders.

In order to decompose the different spillover effects into portion involving the domestic value chain and a portion involving the international value chain, we define the left multiplier in Eq.(14b) as the global multiplier $G \equiv (I_N - \rho W_N)^{-1}$, which represents the global interactions that include the feedbacks through higher order of linkages though neighbors, and define the local multiplier of country s as $H_{ss} \equiv \left(I_Q - \rho W_{ss}\right)^{-1}$. This latter term we call the local multiplier of a country and it represents the domestic interactions of industries within the border of country s. We can define the local multiplier of country r as H_{rr} in the same way. Then the global multiplier G can be decomposed into[7]:

$$G \equiv \begin{bmatrix} G_{ss} & G_{sr} \\ G_{rs} & G_{rr} \end{bmatrix} = \begin{bmatrix} H_{ss} & 0 \\ 0 & H_{rr} \end{bmatrix} + \begin{bmatrix} \rho W_{sr} G_{rs} H_{ss} & G_{sr} \\ G_{rs} & \rho W_{rs} G_{sr} H_{rr} \end{bmatrix}, \tag{17}$$

where the first matrix composed by H_{ss} and H_{rr} in the diagonal in the right of Eq.(17) corresponds to the domestic multiplier, and the second matrix corresponds to the international multiplier which captures the international spillover processes: the off-diagonal blocks represent the diffusions between the two countries and the diagonal blocks represent the country's diffusion firstly go aboard and then feedback to itself. That is, the sub-matrix of $\rho W_{sr} G_{rs} H_{ss}$ corresponds to the process of the technology firstly transmitted from country s to country r directly and then retransmitted back to country s and diffused among the industries within country s.

Following Eq.(14b), the matrix E_k measuring the direct and indirect effects of per-worker capital can be decomposed into a domestic effect, ED_k, and an international effect, EI_k.

$$ED_k \equiv \begin{bmatrix} H_{ss} & 0 \\ 0 & H_{rr} \end{bmatrix} \begin{bmatrix} \alpha & w_{12}(\phi - \rho\alpha) & \dots & w_{1N}(\phi - \rho\alpha) \\ w_{21}(\phi - \rho\alpha) & \alpha & \dots & w_{2N}(\phi - \rho\alpha) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi - \rho\alpha) & w_{N2}(\phi - \rho\alpha) & \cdots & \alpha \end{bmatrix} \tag{18}$$

$$EI_k \equiv$$

$$\begin{bmatrix} \rho W_{sr} G_{rs} H_{ss} & G_{sr} \\ G_{rs} & \rho W_{rs} G_{sr} H_{rr} \end{bmatrix} \begin{bmatrix} \alpha & w_{12}(\phi - \rho\alpha) & \dots & w_{1N}(\phi - \rho\alpha) \\ w_{21}(\phi - \rho\alpha) & \alpha & \dots & w_{2N}(\phi - \rho\alpha) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi - \rho\alpha) & w_{N2}(\phi - \rho\alpha) & \cdots & \alpha \end{bmatrix}. \tag{19}$$

With the matrices of ED_k and EI_k, we can calculate the mean direct, indirect and total domestic effects of per-worker capital expressed as ed_k^{Dir}, ed_k^{Ind} and ed_k^{Tot}

[7] With the definition of G, we have: $(I_N - \rho W_N)\, G = \begin{bmatrix} I_Q - \rho W_{ss} & W_{sr} \\ W_{rs} & I_Q - \rho W_{rr} \end{bmatrix} \begin{bmatrix} G_{ss} & G_{sr} \\ G_{rs} & G_{rr} \end{bmatrix} = \begin{bmatrix} I_Q & 0 \\ 0 & I_Q \end{bmatrix}$ then we can get the relationship of G_{ss} and H_{ss} as $(I_Q + \rho W_{sr} G_{rs}) H_{ss} = G_{ss}$ and the relationship of G_{rr} and H_{rr} $(I_Q + \rho W_{rs} G_{sr}) H_{rr} = G_{rr}$.

respectively, and direct, indirect and total international effects of per-worker capital expressed as ei_k^{Dir}, ei_k^{Ind} and ei_k^{Tot} respectively. Correspondingly, we can get the decomposition results for other inputs and the time trend of productivity.

This two-country setting easily can be extended to a multi-country scenario by setting ED_k as a block diagonal matrix composed of any given number of country blocks. With $EI_k = E_k - ED_k$, one can calculate the corresponding effects for the capital input.

3 Estimation

We outline the estimator for the SAR specification developed in the previous section. The SAR specification associated with Eq.(7) is:

$$y_{it} = \rho \sum_{j=1}^{N} w_{ij} y_{jt} + X'_{it}\beta + Z'_i\gamma + R'_t\delta_0 + R'_t u_i + v_{it}, \tag{20}$$

where w_{ij} is the ij^{th} element of the ($N\times N$) spatial weights matrix W_N, to be given exogenously, u_i is assumed to be an *iid* zero mean random variable with covariance matrix Δ, and v_{it} is an *iid* disturbance term that follows a $N(0,\sigma_v^2)$ distribution. The matrix form of Eq. (20) is given by[8]:

$$y = \rho(W_N \otimes I_T)y + X\beta + \boldsymbol{Z}\gamma + \boldsymbol{R}\delta_0 + QU + V, \tag{21}$$

where y and V are $NT\times 1$ vectors, X is an $NT\times K$ matrix, $\boldsymbol{Z} = (Z\otimes \iota_T)$, Z is an $N\times J$ matrix, ι_T is a T dimensional vector of ones, $\boldsymbol{R} = (\iota_N \otimes R)$, $R = (R_1, R_2, \cdots; R_T)'$, $Q = \iota_N \otimes diag(R)$ is an $NT\times LN$

[8]The observations are stacked with *t* being the fast-running index and *i* the slow-running index, i.e., $y = (y_{11}, y_{12}, \cdots; y_{1T}, \cdots; y_{N1}, \cdots; y_{NT})'$. The order of observations is very important for writing correct codes. In typical spatial analysis literature, the slower index is over time, the faster index is over individuals.

matrix, β is a $K\times 1$ vector, γ is a $J\times 1$ vector, δ_0 is an $L\times 1$ vector, and U is an $LN\times 1$ vector.

The Spatial Durbin specification associated with Eq. (10) is:

$$y_{it} = \rho\sum_{j=1}^{N} w_{ij} y_{jt} + X'_{it}\beta + \sum_{j=1}^{N} w_{ij} X'_{jt}\lambda + Z'_i\gamma + R'_t\delta_0 + R'_t u_i + v_{it}, \qquad (22)$$

where w_{ij} is the ij th element of $(N\times N)$ spatial weights matrix W_N, to be given exogenously, u_i is assumed as iid zero mean random variables with covariance matrix Δ, and v_{it}, is a random noise following $N(0,\sigma_v^2)$ [9]. In addition, the matrix form of Eq.(22) is given by:

$$y = \rho(W_N \otimes I_T)y + X\beta + (W_N \otimes I_T)X\boldsymbol{\lambda} + \boldsymbol{Z}\gamma + \boldsymbol{R}\delta_0 + QU + V, \qquad (23)$$

where y and V are $NT\times 1$ vectors, X is an $NT\times K$ matrix, $\boldsymbol{Z} = (Z\otimes \iota_T)$, Z is $N\times J$ matrix, ι_T is a T dimensional vector of ones, $\boldsymbol{R} = (\iota_N \otimes R)$, $R = (R_1, R_2, \cdots; R_T)'$, $Q = \iota_N \otimes diag(R)$ is an $NT\times LN$ matrix, β is a $K\times 1$ vector, γ is a $J\times 1$ vector, δ_0 is an $L\times 1$ vector, and U is an $LN\times 1$ vector.

Production functions are typically estimated by using various parametric, nonparametric, and semi-parametric techniques. A standard approach to production function estimation is to adhere to the average production technology instead of the best-practice technology, which is accomplished in the stochastic frontier literature by neglecting the assumption that all producers are cost or profit efficient. Minimal differences, if any differences exist at all, usually appear in the estimates of the basic production model parameters, such as in output elasticities, among others. However, the

[9]We may want to specify different spatial correlation structures on dependent variable and independent variables. However, we use the same dependence structure for both variables.

stochastic frontier analysis (SFA) approach can decompose the Solow-type residual into two components. The identification of the decomposition of TFP growth into separate efficiency and technical change components is based on the assumption that the average production function represents the maximum level of output given the levels of inputs on the average. Shifts in this average level of productivity over time, which are usually represented as a common trend by using either a time variable or a time index, indicates technical change. Inefficiency is interpreted as the productivity of a unit at a specific time period relative to the average best-practice production frontier, and it typically includes a one-sided term (negative) that represents the short-fall in a firm's average production relative to a benchmark set by the most efficient firm. One-sided distributions, such as half-normal, truncated normal, exponential, or gamma distribution, are often used in parametric models. Schmidt and Sickles (SS) (1984) and Cornwell, Schmidt, and Sickles (CSS) (1990) suggested the avoidance of strong distributional assumptions by utilizing the structure of a panel production frontier. Schmidt and Sickles (1984) assumed inefficiency to be time-invariant and unit-specific, while Cornwell et al. (1990) relaxed the time-invariant assumption by introducing a flexibly parametrized function of time, thereby replacing individual fixed effects. In the present study, we follow the CSS method as it allows us to estimate time-varying efficiency without requiring further distributional assumptions on the one-sided efficiency term.

The non-spatial CSS model, given in Eq. (4) can be estimated via three techniques: within transformation, generalized least squares, and efficient instrumental variable approach. However, the extended models (Eqs.7 and 10) have several difficulties in estimation because they include additional spatially correlated variables. A quasi-maximum likelihood estimation (QMLE) is thus used in our analysis. QMLE can provide robust standard errors against misspecification of the error distributions. QMLE enables us to minimize the number of parameters to be estimated via the concentrated likelihood function instead of using the full likelihood function. We typically substitute the closed-form solutions of a set of parameters into the likelihood function, and the resultant concentrated likelihood function becomes a function of spatial coefficient parameters only. The optimization with the concentrated likelihood is known to give the same maximum likelihood estimates after maximizing the full likelihood. We will outline the estimation procedure here briefly. The details are presented in Appendix B and are from Han (2016).

We can find closed-form solutions for the parameters, except for the spatial autoregressive parameter ρ, by using the first-order conditions of the likelihood functions of Eqs.7 and 10. The spatial parameters of λ are the coefficients of the spatially weighted independent variables. We treat the spatially weighted independent variables as additional regressors. The substitution of the closed-form solutions into the likelihood functions gives the concentrated likelihood functions with ρ as the only unknown variable. However, $\hat{\rho}$ can be obtained by maximizing the concentrated likelihood function. Hence, all other parameters can be found by using $\hat{\rho}$. Once we obtain the estimates of the parameters β, ρ, δ_i, and σ_v^2, we can recursively solve for an estimate of α_{it}, although we cannot separately identify δ_0 and u_i. By using the estimate of α_{it}, we can obtain the relative inefficiency measure following SS and CSS. In particular, from Eq.??, we know the estimate of α_{it} is $\hat{\alpha}_{it} = R_t'\hat{\delta}_i$.

Estimates of the frontier intercept α_t and the time-dependent relative inefficiency measure u_{it} can be derived as[10]:

[10]Hence, the relative efficiency score can be written as $\widehat{EFF}_{it} = e^{-\hat{u}_{it}}$.

$$\hat{\alpha}_t = \max_j(\hat{\alpha}_{jt}),$$
$$\hat{u}_{it} = \hat{\alpha}_t - \hat{\alpha}_{it}.$$

4 Data

International comparisons of the patterns of output, input and productivity are very challenging (Jorgenson, et al., 2012). We integrate several databases for the empirical analysis of the productivities under the global value chain labor-division network. The countries in our sample are United States, China, Japan, Korea and India, which are the main economies in the Asia & Pacific area. The international production network has rapidly developed among these countries since 1980's. We extract the output measures of gross output and input measures of capital service, labor service and intermediate input from the KLEMS database.

The WORLD KLEMS database provided the quantity and price indices data for the United States, Japan, Korea and India. 2005 is the reference year[11]. Data for China are collected from the China Industrial Productivity (CIP) Database, which provided the real and nominal gross output and intermediate input by reconstructing China's input-output table (Wu and Keiko, 2015; Wu, 2015; Wu, et al, 2015). We calculate the growth rates for gross output and intermediate input in constant prices by single deflation. CIP also provided the capital and labor input indices which are consistent with the KLEMS database and we converted the reference year from 1990 to 2005.

The inter-country input-output data are draw from the World Input-Output database (WIOD) database. We match and aggregate some industries since there are some difference in the industry classification across the databases of KLEMS, WIOD and CIP, although they are all broadly consistent with the ISIC revision 3. The nominal volumes

[11] In Asia KLEMS database, the reference years of the indices for Korea is 2000, and the labor and capital indices for Korea is 1981. The reference years for other indices are 2005, which is in accordance with US KLEMS data.

for each index are used to generate the weights for calculating the input and output indices of the aggregated industries. We omitted non-market economy industries, which are mostly local public services that include Housing, Public Administration and Defense, Education, Health and Social Work, Other Community, Social and Personal Services[12]. The industry classifications we use are listed in Table 1. The sample period is 1980-2010. We extract industry-level linkages among the five countries from the input-output table for 1995, which is the mid-year of the sample period.

Table 1: Industry classifications and codes

No.	Industry	ISIC Rev. 3
1	Agriculture, Hunting, Forestry and Fishing	AtB
2	Mining and Quarrying	C
3	Food , Beverages and Tobacco	15t16
4	Textiles and Textile, Leather, leather and footwear	17t19
5	Wood and of Wood and Cork	20
6	Pulp, Paper, Paper , Printing and Publishing	21t22
7	Coke, Refined Petroleum and Nuclear Fuel	23
8	Chemicals and Chemical	24
9	Rubber and Plastics	25
10	Other Non-Metallic Mineral	26
11	Basic Metals and Fabricated Metal	27t28
12	Machinery, Nec	29

[12] We also remove the whole and retail trade, Renting of Machine and Equipment and Other Business Activities in India for the data are missing.

13	Electrical and Optical Equipment	30t33
14	Transport Equipment	34t35
15	Manufacturing Nec; Recycling	36t37
16	Electricity, Gas and Water Supply	E
17	Construction	F
18	Wholesale and Retail trade	50to52
19	Hotels and Restaurants	H
20	Transport, storage & post services	60t64
21	Financial Intermediation	J
22	Renting of Machine and Equipment and Other Business Activities	71t74

International trade has been an important channel for transmitting growth across countries (Ho, et al., 2013). Coe and Helpman (1995) show that domestic productivity depends on the import share of a weighted sum of R&D expenditure in other countries. Ertur and Koch (2011) use the average bilateral trade flow as spatial weight matrix in the technological interdependence study of economic growth. We use the inter-industry intermediate flows in the World input-output table to construct the spatial weight matrix on an industry level, as the intermediates embody technical know-how and are the main drivers in acquiring knowledge from other industries through domestic and international supply chains. For this reason we use the lower triangular matrix of the input-output table to present the channel of spillover that based on the inputs from upstream industries.

We also examine the channel of spillovers through production for downstream industries by exploiting the upper triangular matrix. The spatial weights matrices are expressed as $W1$ with elements of $w_{ij} = w_{ji} = IO_{ij}$ for $\forall i > j$, indicating intermediate inputs from industry i to industry j in nominal US dollar values, and $W2$ with elements of $w_{ij} = w_{ji} = IO_{ij}$ for $\forall j > i$, indicating intermediate outputs of industry i to industry j. The diagonal elements of $W1$ and $W2$ are all 0. Elhorst (2001) propose a normalization method by dividing the matrix by the maximum eigenvalue when row normalization may cause the matrix to lose its economic interpretation of distance decay. However, in this paper, we assumes that the productivity spillover is dependent on the share weighted sum of the productivity of their intermediate suppliers (or users)[13], which is consistent with the seminal article of Coe and Helpman (1995). Therefore, $W1$ and $W2$ are row normalized to generate the spatial weight matrix.

5 Empirical results

We model the industry-specific productivity growth with $R(t)'\delta_i = \delta_i t$ to and country dummies to control for different technology states in different countries. To avoid possible endogeneity problems between input factor levels and productivity, we lag the inputs one period (Ackerberg, et al., 2015). In order to control for possible endogeneity between spatial linkages and output, we use the input-output table in the mid-year of the sample period (i.e. 1995) to construct the spatial weight matrices following the spatial literature that address the constructions of socioeconomic weight matrices (Case, et al., 1993; Cohen and Paul, 2004).

[13] This is more intuitive than assuming spillover to be proportional to the value of linkage, by normalizing the weight matrix by maximum eigenvalue, i.e. small enterprise may be more influenced by its major supplier or customer than big enterprise, although big company may use more products from the same supplier (or sell more products to the same customer) than the small company.

5.1 Estimations of Production Functions

In Table 1, we provide estimates of the Solow-type production function for the industries for our selected countries, without a spatial specification in Eq. (4). We use the Cornwell, Schmidt, Sickles (CSS) (1990) estimator. The CSS estimator with time-varying fixed effects (CSSW), and its special case of time-invariant fixed effects introduced by Schmidt and Sickles (SS), are based on standard projections used in the average production approach but with the added option to decompose the error term from the within residuals after, e.g., a fixed effects regression. In the stochastic frontier analysis paradigm, when no scale economies exist, and they do not appear to be in this analysis, TFP change = technical change (coefficient of year dummies) + technical efficiency change (CSS estimated efficiency). When estimating the average production function, we estimate the coefficients and TFP as the Solow residual. One other aspect of the SS and the CSS slope estimates is that they also are semiparametric efficient when the joint distribution of the effects and the regressors are specified non-parametrically and are equivalent to the standard panel fixed effect estimates when the fixed effects and means of the regressors are correlated, such as in the Mundlak and Pesaran setups (Park, Sickles, and Simar (JOE, 1998, 2003, 2007). However, use of the decomposition of TFP into efficiency and an innovation component is often useful and informative.

The dependent variable is gross-output index. All coefficient estimates for the factor inputs are statistically significant. The coefficients of inputs can be interpreted as output elasticities. The elasticity of intermediate input is the largest, while capital is the smallest. We also can estimate the parameters for the time trend of productivity in the CSS random effects model (CSSG). Hausman-Wu statistic for the fixed effects v. random effects specification of the CSS estimator is 22.408 with a p-value of 0.803 and thus we do not reject the time-varying random effects specification. The coefficient on the *Time* variable is about 0.009 which implies the average growth rate of the economy is about 0.9% in this period.

TABLE 1

Estimate of Non-spatial Cobb-Douglas Production Function

	(1)	(2)
Variables	CSSW	CSSG
lnk(α)	.110***	.108***
	(.012)	(.011)
lnm(β)	.576***	.591***
	(.011)	(.010)
Country-dummy	No	Yes
Year-dummy	Yes	Yes
Intercept		-0.084*
		(.044)
Time		.009***
		(.002)
Implied γ	.314	.301
# of industries	108	108
# of obs.	3132	3132

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

The first and last four columns of Table 2 provide estimates of the SAR and SDM specified production functions with spatial spillovers based on Eq. (8) and Eq. (10), respectively. All of the coefficients for the factor inputs in the SAR and SDM specifications are statistically significant at the 1% significance level. The coefficient of the spatially lagged dependent variable ρ is estimated in a range of 0.223 to 0.287 for SAR and 0.283 to 0.348 for SDM.. The parameters of ϕ and φ, which represent the local spatial relationships of factor inputs, can be calculated based on the expressions in Eq. (10). In the SDM-upstream model, ϕ and φ are both positive, whereas the coefficient of the spatially weighted capital input is not significant. In the SDM-downstream model, the coefficients of the spatially weighted independent variables are significant, and ϕ and φ are negative and positive respectively, which suggests that the neighbour's capital and intermediate inputs have a negative and positive effect respectively for the productivity of an industry. The intuitive implication for a negative effect is related to the indirect effect that we more fully explain in Section 5.2 below.

TABLE 2

Estimate of SAR and SDM Production Function

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SAR-upstream		SAR-downstream		SDM-upstream		SDM-downstream	
	CSSW	CSSG	CSSW	CSSG	CSSW	CSSG	CSSW	CSSG
lnk	.094***	.094***	.103***	.101***	.098***	.096***	.108***	.107***
	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)
lnm	.568***	.583***	.566***	.580***	.568***	.583***	.570***	.583***
	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)
W•lnk					.016	.011	-.042*	-.052**
					(.039)	(.033)	(.024)	(.022)
W•lnm					-.137***	-.090**	-.136***	-.077**
					(.048)	(.045)	(.036)	(.034)
Country-dummy	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Year-dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Intercept		.009		.005		-.005		-.040
		(.044)		(.043)		(.047)		(.045)
Time		.001		.002		.002		.005**
		(.002)		(.002)		(.002)		(.002)
W•lny(ρ)	.287***	.259***	.239***	.223***	.348***	.302***	.331***	.283***
	(.026)	(.019)	(.021)	(.017)	(.031)	(.031)	(.025)	(.025)
σ_v^2	.009	.009	.009	.009	.009	.009	.009	.009
R^2	.814	.817	.819	.824	.812	.816	.815	.819
Adjusted R^2	.798	.802	.804	.808	.796	.799	.799	.803
LL	2988.595	2897.538	2994.418	2905.608	2993.257	2901.253	3009.440	2918.744

Implied γ	.337	.323	.331	.318	.334	.321	.321	.311
Implied ϕ					.050	.040	-.006	-.021
Implied φ					.061	.087	.053	.088

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

The *intercept* terms estimated with the CSSG model are positive in the SAR model and negative in SDM model but insignificantly different from zero. In the SAR and SDM-upstream model, the coefficients for linear *time trends* for both specifications of spatial weight matrices are small and insignificant from zero. However, in the SDM-downstream model, the estimated parameter for the time trend is 0.005 which is significantly different from zero for the spatial weight matrices specified by the output intermediate flows.

In Figure 2 we calculate aggregate productivity growth for the five countries based on the CSSG estimation of the non-spatial, SAR and SDM models. Domar weights are used for the aggregation of economy-wide productivity growth that was introduced and developed by Domar (1961) and Hulten (1978). The weights account for the effects of productivity changes of an individual industry on those downstream industries that benefit from more efficiently produced intermediate inputs[14]. The weighted average growth in the non-spatial model is higher than the SAR models and is close to the SDM models. We can compare the goodness-of-fit of the SAR and SDM model using the likelihood ratio test as SAR is nested in SDM. The LR test statistics are 7.43 and 26.27 for the input and output spatial weight matrices, respectively, which suggests that the

[14] To be consistent with general practices in the growth literature, we follow the methodology suggested by OECD (2001) to calculate the Domar weights by considering each country as a closed economy. This does not take account of the productivity change effect that comes from the imported intermediate inputs during our aggregation process on the country level. The imported intermediates and intra-industry flows are removed from the gross output for the calculation of Domar weights. We also provide the aggregation result with Domar weights that consider each country as an open economy and incorporate the influence of productivity change of imported intermediate inputs and simple gross output weighted average productivity change on country level in Appendix D.

SDM specification is more statistically significant than SAR specification, which in turn implies that there exist capital and intermediate externalities in the growth process. Therefore, the models with spatial weighted independent variables are the appropriate specification for the samples[15]. Furthermore, the partial Spatial Durbin model with the spatial weight matrix based on downstream linkages is our preferred model because it yields the highest log likelihood values. The estimated technical change in the SDM-downstream model suggests that China has the fastest aggregate productivity growth of 2.64%. But comparing this with the value of 3.86% in the non-spatial model, ignoring the spatial interactions appears to leads to an overestimation of China's productivity growth. However, for the developed countries, such as the US and Japan, the non-spatial model results indicate a much lower level of TFP growth rates. They are 0.87% and 0.61% in the non-spatial model and 1.36% and 1.33% respectively in SDM-downstream model.

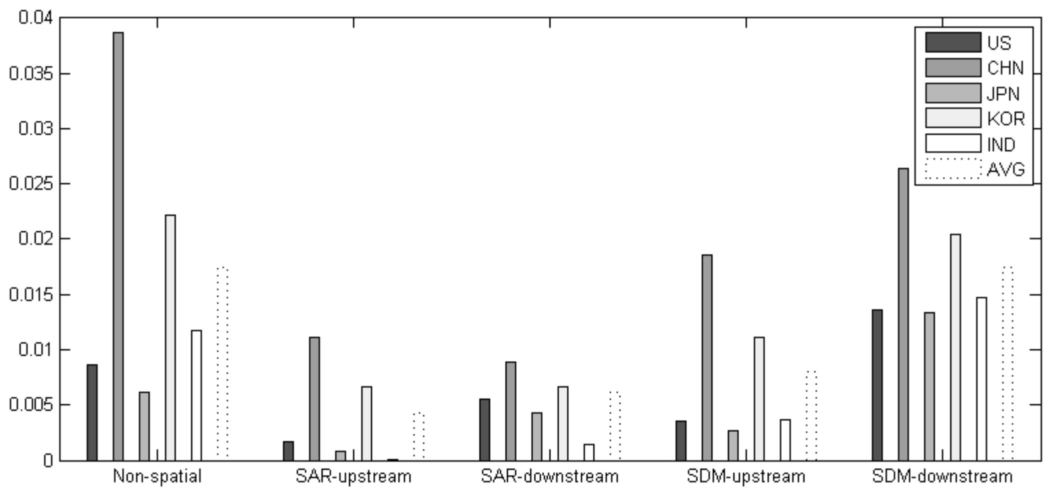
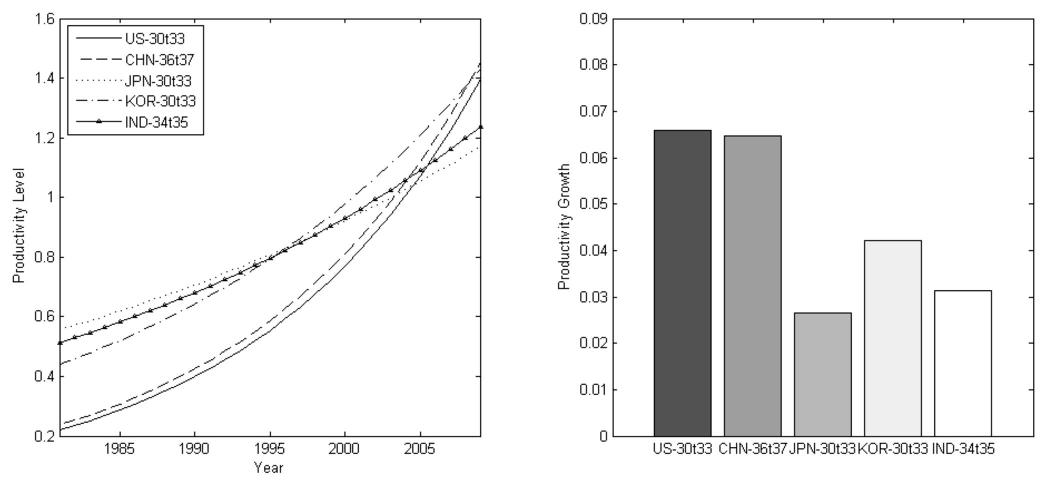


FIGURE 2

Aggregate productivity growth of each country by model

[15] The unrealistic assumption of a common ratio of the direct and indirect elasticities for all production factors in the SAR model, as discussed by Elhorst (2014) and Glass et al. (2015), may lead to misspecification in empirical studies of economic growth.

The productivity level and growth of each industry can be measured based on the CSSG estimations of the SDM-downstream model. In the US, the industry of *Electrical and Optical Equipment* (30t33) exhibits the most rapid productivity growth not only in US but also in the world with a growth rate of 6.6%, whereas the industry of *Construction* (F) is the lowest and falls at the rate of -1.2%. *Electrical and Optical Equipment* (30t33) is also the fastest growing industry in both Japan and Korea, with a 2.7% and 4.2% growth rate respectively. *Manufacturing Nec and Recycling* (36t37) in China and *Transport Equipment* (36t37) in India show the most rapid growth in each country at 6.5% and 3.1% respectively. In Figure 3 we list the industries that exhibit the highest productivity growth in the five countries based on our preferred SDM-downstream model.



(a) Productivity Level (b) Productivity Growth

FIGURE 3

Highest Productivity Growth Industries in Five Countries

5.2 The elasticity of input factors and spatial spillovers

The coefficients of the independent variables represent the output elasticities of input factors in a non-spatial production function setting. Whereas, when cross-section interaction exists, the output change of one industry due to the adjustment of the factor input should not only consider changes in the factor input itself, but also induced changes in its neighbor's inputs. Therefore the output elasticity for the all the industries should be a $N \times N$ matrix. As suggested by LeSage and Pace (2009), we diagonalize the coefficient of independent variables and add the local interaction from neighbor's inputs, then multiply the inverse matrix, $(I_N - \rho W)^{-1}$, to derive the expressions for the matrix-formed output elasticity of input factors given in Eq. (14). Hence, an elasticity in a spatial setting includes two parts: the internal elasticity expressed by the direct effect, which is the average along the diagonal, and external elasticity measured by the indirect effect, which is the average of the row (or column) sums of the off-diagonal elements. Average total output elasticity is expressed by the sum of the direct and indirect effects. We calculate the direct, indirect and total effects. To test for the significance of these effects, we follow the algorithms LeSage and Pace (2009) suggested by drawing parameter estimates 1000 times based on the variance-covariance matrix of the parameters to get the corresponding distribution of these effects, and then we compute their means and standard deviations based on the simulation.

The top row of Table 2 shows the internal, external and total output elasticity of each factor input in the SDM-downstream model. The internal elasticities of capital and intermediate inputs are 0.109 and 0.590 respectively and both are statistically significant, which is approximately consistent with the results in the non-spatial model. The external elasticities reflect the spillover effects of the input factors. From the perspective of industry production, the spillover effects are two-fold. When the factor input of industry *A* is increased, the output of its neighbor, industry *B*, may decrease because of factor scarcities. However, the increased input of industry *A* will also increase industry *A*'s output, which will improve the supply of industry *A*'s intermediate inputs for industry *B* through the industrial linkages and hence increase the output of industry *B*. The external elasticities of capital and intermediate inputs in Table 2 are 0.051 and 0.193 respectively, which suggest that the complementary relationship on capital and intermediate input outweighs the competitive relationship among industries for scarce inputs, which implies that the output of the industry may benefit when its neighbor industries are expanding their capital and intermediate inputs. The output elasticity of the labor input can be decomposed into its internal and external portions, which are 0.302 and -0.244, resulting in a total elasticity of 0.058. The negative external elasticity suggests a negative spillover effect of a neighbor industry's labor input.

TABLE 2

Internal, External and Total Elasticity of input factors

SDM-downstream		Internal		External		Total	
		Elasticity	asy.t-stat	Elasticity	asy.t-stat	Elasticity	asy.t-stat
	Capital	0.109***	9.810	0.051***	3.123	0.160***	7.097
overall	Intermediate	0.590***	58.188	0.193***	6.510	0.783***	23.509
	Labor	0.302	-	-0.244	-	0.058	-
	Capital	0.109***	9.810	0.048***	3.129	0.156***	7.257
domestic	Intermediate	0.590***	58.192	0.181***	6.589	0.770***	24.722
	Labor	0.302	-	-0.228	-	0.073	-
	Capital	0.000***	2.878	0.003***	3.031	0.003***	3.030
international	Intermediate	0.000***	4.568	0.013***	5.525	0.013***	5.523
	Labor	0.000	-	-0.016	-	-0.016	-

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

We next decompose the elasticities based on Eq. (18) and Eq. (19) in order to measure the spillovers that spread among domestic and international industries separately. As shown in the last 2 rows of Table 2, for the internal elasticity, the international part is negligible because only a small part of the feedback component in the direct effect can be attributed to the international linkage. From the decomposition of the external elasticity, however, we find that international spillovers constitute about 6.5% of the external elasticity for each of the factor inputs. Since the calculation is based on a time-invariant specification of the spatial weight matrix in 1995, and the growth of international intermediate trade has been much higher than the growth of world GDP since then, we may expect an increasing trend for the international part in the overall spillover[16].

5.3 Hicks-neutral technical change and spatial spillovers

One advantage of our spatial model with heterogenetic technical change is that we can estimate the industry-specific Hicks-neutral technical change and its direct and indirect effect in the global value chain setting. Complete empirical results of Hicks-neutral technical change in the SDM-downstream model for all cross-sectional samples are displayed in Table 3. The Domar-weighted aggregate of the five countries are shown in Figure 4. The direct and indirect effects, and their decompositions into domestic and international spillovers, are constructed from Eq. (15b) and Eq. (19). Standard errors for the direct and indirect effects are based on simulations wherein we bootstrap 1000 times to calculate the variance-covariance matrix for δ_i and other parameters in SDM model, then follow same process as LeSage and Pace (2009) to get significance levels.

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[16] We estimate the model with spatial weight matrix constructed by the world input-output table of 2010. The international spillovers constitute about 9.8% of the external elasticity of each factor inputs. The elasticity results are given in Appendix C.

The left side of Figure 4 represents the technological growth measured by the direct and indirect effects from the receiving perspective. The direct effect represents the technological growth by the industry itself that mostly comes from the independent innovation or improvement within the industry. On country level, China exhibits the most rapid internal technological growth measured by the direct effect at 5.92%, while the growth rates for Korea, India, Japan and US are 4.78%, 4.09%, 3.89% and 3.84%, respectively. The indirect effects represent the Hicks-neutral technology spillovers that industries receive through producing intermediate inputs for their user industries. The weighted average indirect effects for China, Korea, India, US and Japan are 2.68%, 1.90%, 1.60%, 1.56% and 1.44%, respectively. The spillovers received account for 27% to 31% of the total technological growth of the countries in our sample.

TABLE 3

Technical change and spatial spillovers for SDM-downstream model

	Direct	Received				Offered			
		Indirect			Total	Indirect			Total
		Sum	Domestic	Int'l		Sum	Domestic	Int'l	
US.s1	0.0308***	0.0058**	0.0053**	0.0006**	0.0366***	0.0135**	0.0108**	0.0027**	0.0443***
US.s2	0.0212***	0.0086***	0.0084***	0.0002**	0.0298***	0.0082**	0.0078**	0.0004**	0.0294***
US.s3	0.0172***	0.0082***	0.0080***	0.0002*	0.0254***	0.0083**	0.0075**	0.0007**	0.0255***
US.s4	0.0216***	0.0088***	0.0085***	0.0004**	0.0304***	0.0033**	0.0028**	0.0005**	0.0249***
US.s5	0.0117*	0.0067**	0.0064***	0.0003**	0.0184***	0.0023***	0.0021***	0.0002***	0.0140*
US.s6	0.0085	0.0098***	0.0094***	0.0004**	0.0183***	0.0041***	0.0035***	0.0006***	0.0126***
US.s7	0.0319***	0.0072***	0.0070***	0.0002**	0.0391***	0.0137**	0.0126***	0.0012**	0.0456***
US.s8	0.0150***	0.0094***	0.0086***	0.0008***	0.0244***	0.0065*	0.0048*	0.0017*	0.0215***
US.s9	0.0193***	0.0084***	0.0082***	0.0002*	0.0277***	0.0078**	0.0073**	0.0005**	0.0271***
US.s10	0.0219***	0.0063**	0.0061**	0.0002*	0.0282***	0.0036**	0.0033**	0.0003*	0.0255***
US.s11	0.0187***	0.0091***	0.0088***	0.0003**	0.0277***	0.0132**	0.0122**	0.0010*	0.0319***
US.s12	0.0146***	0.0080***	0.0076***	0.0004**	0.0226***	0.0048*	0.0041*	0.0008*	0.0195***
US.s13	0.0795***	0.0072***	0.0059***	0.0013***	0.0867***	0.0439***	0.0332***	0.0107**	0.1234***
US.s14	0.0175***	0.0104***	0.0101***	0.0003**	0.0279***	0.0099*	0.0090**	0.0010**	0.0274***
US.s15	0.0310***	0.0078***	0.0076***	0.0002*	0.0388***	0.0058**	0.0054**	0.0004*	0.0368***
US.s16	0.0171***	0.0085***	0.0085***	0.0001***	0.0256***	0.0037**	0.0036**	0.0001**	0.0208***
US.s17	0.0014	0.0092***	0.0091***	0.0001***	0.0107*	0.0009*	0.0009*	0.0000*	0.0024*
US.s18	0.0320***	0.0081***	0.0080***	0.0002*	0.0401***	0.0194***	0.0185***	0.0009***	0.0513***
US.s19	0.0146***	0.0079***	0.0079***	0.0001***	0.0225***	0.0066*	0.0063*	0.0002*	0.0211**
US.s20	0.0247***	0.0086***	0.0082***	0.0004**	0.0333***	0.0159**	0.0138**	0.0021**	0.0406***
US.s21	0.0188***	0.0085***	0.0081***	0.0004**	0.0273***	0.0018**	0.0014**	0.0003*	0.0206***
US.s22	0.0093	0.0083***	0.0081***	0.0002**	0.0176***	0.0027***	0.0024***	0.0003***	0.0120***
CN.s1	0.0002	0.0136***	0.0133***	0.0003**	0.0138**	-0.0000**	-0.0000**	-0.0000**	0.0002**
CN.s2	-0.0178***	0.0114***	0.0110***	0.0004**	-0.0065**	-0.0091**	-0.0087**	-0.0004*	-0.0269***
CN.s3	0.0490***	0.0028***	0.0025***	0.0003*	0.0518***	0.0252***	0.0244***	0.0008*	0.0742***
CN.s4	0.0423***	0.0091***	0.0080***	0.0011**	0.0514***	0.0170***	0.0127***	0.0043***	0.0594***
CN.s5	0.0645***	0.0097***	0.0093***	0.0004**	0.0743***	0.0089***	0.0085***	0.0005**	0.0735***
CN.s6	0.0432***	0.0106***	0.0102***	0.0004**	0.0538***	0.0089***	0.0085***	0.0004**	0.0521***
CN.s7	0.0186***	0.0061**	0.0059**	0.0002**	0.0247***	0.0066**	0.0065**	0.0001**	0.0252***
CN.s8	0.0457***	0.0110***	0.0106***	0.0004**	0.0567***	0.0185***	0.0178***	0.0007**	0.0642***
CN.s9	0.0452***	0.0138***	0.0134***	0.0004**	0.0589***	0.0155***	0.0149***	0.0006*	0.0607***
CN.s10	0.0500***	0.0066***	0.0064***	0.0002*	0.0566***	0.0285***	0.0278***	0.0006*	0.0785***
CN.s11	0.0415***	0.0107***	0.0103***	0.0004**	0.0523***	0.0338***	0.0326***	0.0012**	0.0753***
CN.s12	0.0495***	0.0125***	0.0122***	0.0003**	0.0620***	0.0193***	0.0188***	0.0005*	0.0688***
CN.s13	0.0498***	0.0126***	0.0113***	0.0013***	0.0624***	0.0228***	0.0213***	0.0015**	0.0726***
CN.s14	0.0594***	0.0124***	0.0121***	0.0003**	0.0718***	0.0155***	0.0151***	0.0004*	0.0749***
CN.s15	0.0780***	0.0127***	0.0123***	0.0003**	0.0907***	0.0077***	0.0073***	0.0004**	0.0856***
CN.s16	0.0109**	0.0059**	0.0057**	0.0002*	0.0168***	0.0018*	0.0018*	0.0000*	0.0127**
CN.s17	0.0048	0.0146***	0.0145***	0.0002*	0.0195***	0.0031***	0.0031***	0.0000***	0.0080***
CN.s18	0.0017	0.0131***	0.0127***	0.0003**	0.0147**	0.0006**	0.0006**	0.0000**	0.0023**
CN.s19	-0.0036	0.0088***	0.0086***	0.0002*	0.0052*	-0.0008*	-0.0008*	-0.0000*	-0.0045*
CN.s20	0.0106*	0.0100***	0.0091***	0.0008**	0.0205***	0.0053***	0.0049***	0.0005***	0.0159*
CN.s21	0.0036	0.0076**	0.0060**	0.0016***	0.0112*	0.0003*	0.0002*	0.0001*	0.0038*
CN.s22	-0.0152**	0.0102***	0.0097***	0.0005**	-0.0050**	-0.0021*	-0.0021*	-0.0000*	-0.0173**
JP.s1	0.0239***	0.0054**	0.0052**	0.0003**	0.0293***	0.0076**	0.0072**	0.0004**	0.0315***
JP.s2	0.0207***	0.0071***	0.0070***	0.0002*	0.0278***	0.0030**	0.0028**	0.0002**	0.0237***
JP.s3	0.0146**	0.0067**	0.0063**	0.0004**	0.0213***	0.0071*	0.0067*	0.0004*	0.0217**
JP.s4	0.0077	0.0086***	0.0073***	0.0013***	0.0163**	0.0010**	0.0006**	0.0003**	0.0087**
JP.s5	0.0179***	0.0063***	0.0059***	0.0004**	0.0242***	0.0040*	0.0037*	0.0004*	0.0219***
JP.s6	0.0113*	0.0084***	0.0081***	0.0003*	0.0197***	0.0042***	0.0039***	0.0003***	0.0155*
JP.s7	0.0117**	0.0082***	0.0079***	0.0003*	0.0199***	0.0039*	0.0034*	0.0005*	0.0156**
JP.s8	0.0236***	0.0073***	0.0065***	0.0008**	0.0308***	0.0101**	0.0074**	0.0027**	0.0337***
JP.s9	0.0150***	0.0086***	0.0083***	0.0004*	0.0236***	0.0070**	0.0064**	0.0007**	0.0221***
JP.s10	0.0229***	0.0062***	0.0060***	0.0003*	0.0291***	0.0060**	0.0053**	0.0007*	0.0289***
JP.s11	0.0175***	0.0074***	0.0069***	0.0005**	0.0249***	0.0154**	0.0131**	0.0023*	0.0329***

JP.s12	0.0260***	0.0079***	0.0072***	0.0008**	0.0340***	0.0087**	0.0070**	0.0017**	0.0347***

TABLE 3 *(Continued)*

	Direct	Received				Offered			
		Indirect			Total	Indirect			Total
		Sum	Domestic	Int'l		Sum	Domestic	Int'l	
JP.s13	0.0397***	0.0082***	0.0064***	0.0019***	0.0479***	0.0207***	0.0151***	0.0056**	0.0604***
JP.s14	0.0199***	0.0087***	0.0082***	0.0005**	0.0286***	0.0080*	0.0068**	0.0012*	0.0278***
JP.s15	0.0142**	0.0075***	0.0072***	0.0004**	0.0217***	0.0016***	0.0015*	0.0002*	0.0158**
JP.s16	0.0311***	0.0071***	0.0070***	0.0001***	0.0382***	0.0100**	0.0096***	0.0004***	0.0411***
JP.s17	0.0110**	0.0075***	0.0072***	0.0003**	0.0185***	0.0120*	0.0113*	0.0008*	0.0231**
JP.s18	0.0273***	0.0071***	0.0068***	0.0003**	0.0344***	0.0230**	0.0216**	0.0013*	0.0502***
JP.s19	0.0109*	0.0077***	0.0075***	0.0002*	0.0186***	0.0059***	0.0057***	0.0002***	0.0168*
JP.s20	0.0214***	0.0074***	0.0071***	0.0003**	0.0289***	0.0112**	0.0103**	0.0009*	0.0326***
JP.s21	0.0183***	0.0076***	0.0073***	0.0003**	0.0259***	0.0019**	0.0017**	0.0002*	0.0202***
JP.s22	0.0151***	0.0073***	0.0071***	0.0002*	0.0224***	0.0034*	0.0033*	0.0001*	0.0185***
KR.s1	0.0203***	0.0060**	0.0051**	0.0008*	0.0263***	0.0074**	0.0072**	0.0002**	0.0277***
KR.s2	0.0490***	0.0089***	0.0084***	0.0005***	0.0579***	0.0034***	0.0034***	0.0001***	0.0524***
KR.s3	0.0169***	0.0070**	0.0056**	0.0014**	0.0238***	0.0060**	0.0057**	0.0003**	0.0228***
KR.s4	0.0214***	0.0091***	0.0042***	0.0050***	0.0305***	0.0035**	0.0027**	0.0008**	0.0248***
KR.s5	0.0252***	0.0065**	0.0056**	0.0008*	0.0317***	0.0025**	0.0024**	0.0001*	0.0277***
KR.s6	0.0157***	0.0085***	0.0074***	0.0012**	0.0242***	0.0044**	0.0043**	0.0001**	0.0201***
KR.s7	0.0236***	0.0090***	0.0084***	0.0007***	0.0327***	0.0107**	0.0105**	0.0003*	0.0344***
KR.s8	0.0319***	0.0091***	0.0070***	0.0021**	0.0410***	0.0129**	0.0119**	0.0010**	0.0448***
KR.s9	0.0139**	0.0105***	0.0092***	0.0013**	0.0244***	0.0051*	0.0049*	0.0002*	0.0190**
KR.s10	0.0283***	0.0076***	0.0068***	0.0008*	0.0360***	0.0121***	0.0118***	0.0003*	0.0405***
KR.s11	0.0212***	0.0088***	0.0073***	0.0015**	0.0300***	0.0134**	0.0128**	0.0006*	0.0345***
KR.s12	0.0317***	0.0091***	0.0070***	0.0020**	0.0408***	0.0094**	0.0089**	0.0005**	0.0411***
KR.s13	0.0557***	0.0111***	0.0052***	0.0059***	0.0668***	0.0251***	0.0228***	0.0024**	0.0808***
KR.s14	0.0300***	0.0104***	0.0081***	0.0023**	0.0404***	0.0107**	0.0101**	0.0006*	0.0408***
KR.s15	0.0194***	0.0080***	0.0068***	0.0012**	0.0275***	0.0040**	0.0039**	0.0001*	0.0235***
KR.s16	0.0324***	0.0073**	0.0066***	0.0008*	0.0397***	0.0081***	0.0080***	0.0001*	0.0406***
KR.s17	0.0039	0.0102***	0.0089***	0.0013**	0.0141**	0.0031**	0.0031**	0.0001**	0.0070**
KR.s18	0.0226***	0.0087***	0.0074***	0.0013**	0.0312***	0.0061**	0.0059**	0.0002*	0.0287***
KR.s19	0.0051	0.0097***	0.0087***	0.0009**	0.0147**	0.0018**	0.0018**	0.0000**	0.0069**
KR.s20	0.0266***	0.0081***	0.0063***	0.0018**	0.0347***	0.0147**	0.0135***	0.0011**	0.0413***
KR.s21	0.0192***	0.0093***	0.0082***	0.0011**	0.0286***	0.0009**	0.0009**	0.0000*	0.0202***
KR.s22	-0.0003	0.0096***	0.0086***	0.0011**	0.0094**	-0.0000**	-0.0000**	-0.0000**	-0.0003**
IN.s2	0.0233***	0.0079***	0.0077***	0.0002*	0.0312***	0.0215**	0.0213**	0.0002*	0.0448***
IN.s3	0.0136**	0.0080***	0.0078***	0.0002*	0.0216***	0.0046*	0.0045*	0.0000*	0.0181**
IN.s4	0.0263***	0.0081***	0.0079***	0.0002**	0.0344***	0.0092**	0.0091**	0.0001*	0.0354***
IN.s5	0.0283***	0.0088***	0.0083***	0.0006**	0.0371***	0.0081**	0.0079**	0.0002**	0.0364***
IN.s6	-0.0208***	0.0078**	0.0076**	0.0002*	-0.0130*	-0.0044**	-0.0044**	-0.0000*	-0.0252***
IN.s7	0.0174***	0.0080***	0.0074***	0.0006**	0.0254***	0.0020**	0.0020**	0.0000**	0.0195***
IN.s8	0.0075	0.0077***	0.0076***	0.0001***	0.0152**	0.0040**	0.0040**	0.0000**	0.0116**
IN.s9	0.0288***	0.0084***	0.0078***	0.0006**	0.0372***	0.0105***	0.0103***	0.0002**	0.0392***
IN.s10	0.0215***	0.0093***	0.0090***	0.0004**	0.0308***	0.0052**	0.0051**	0.0001*	0.0267***
IN.s11	0.0339***	0.0050**	0.0047**	0.0003**	0.0389***	0.0086**	0.0085**	0.0001**	0.0425***
IN.s12	0.0352***	0.0074***	0.0072***	0.0002**	0.0426***	0.0344***	0.0342***	0.0002*	0.0696***
IN.s13	0.0056	0.0106***	0.0101***	0.0005**	0.0162**	0.0013**	0.0013**	0.0000**	0.0069**
IN.s14	0.0446***	0.0095***	0.0088***	0.0007***	0.0541***	0.0058**	0.0058***	0.0001**	0.0505***
IN.s15	0.0237***	0.0093***	0.0090***	0.0004**	0.0330***	0.0095**	0.0094**	0.0001*	0.0331***
IN.s16	0.0346***	0.0104***	0.0101***	0.0003**	0.0449***	0.0093**	0.0092**	0.0001**	0.0439***
IN.s17	0.0350***	0.0070***	0.0067***	0.0003**	0.0420***	0.0114***	0.0113***	0.0001**	0.0464***
IN.s19	0.0066	0.0084***	0.0081***	0.0003**	0.0150**	0.0043**	0.0043**	0.0000**	0.0109**
IN.s20	0.0302***	0.0088***	0.0087***	0.0001*	0.0390***	0.0044**	0.0043**	0.0000*	0.0346***
IN.s21	0.0174***	0.0081***	0.0078***	0.0003**	0.0255***	0.0107**	0.0106**	0.0001*	0.0281***
IN.s22	0.0274***	0.0080***	0.0078***	0.0002**	0.0354***	0.0010**	0.0010**	0.0000**	0.0284***

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

By decomposing the indirect effects into domestic and international spillovers, Korea is found to have benefited most from international spillovers, with an international indirect effect of 0.41%, which constitutes 21.5% of the total spillovers that Korea's industries received. Japan has an international effect of 0.08%, which constitutes 5.6% of the total spillover Japan's industries received. The international parts are relatively small for the remaining three countries, with less than 5% in total received spillovers.

The right side of Figure 4 represents the technological growth of each country from the offering perspective. The direct effects are comparable to values on the left side of Figure 4. The aggregated–indirect effects for China, Japan, India, Korea and US are 2.72%, 2.12%, 2.09%, 1.88% and 1.79%[17]. However, the international spillovers that each country offers are different from those that they receive. The US and Japan contribute the most international spillovers with a growth impact of 2.15‰ and 1.94‰, which accounts for 10.83% and 10.14% of their total offered spillovers. The international spillovers for China, Korea and India are 1.41‰, 1.21‰ and 0.18‰. Our results suggest that while China is the most rapidly growing economy in the world, the developed countries, such as US and Japan, still contribute the most to international knowledge diffusion[18]. Combined with the results of the international spillovers received by each country, we can find that US and Japan made the most net contributions with net international spillovers at 1.37‰ and 1.34‰, followed by China at 0.19‰. Korea benefits most with net international spillovers at -2.88‰.

The relatively small role for India in terms of international spillovers is mirrored by its relatively small international indirect effect of 0.18‰, which is only 2% of its indirect

[17] The summation of indirect effect received and offered are not equal because the average is weighted by the output of the industries.

[18] We calculate the technological growth components with estimates based on the 2010 input-output tables and found China and US had become the net contributors for international knowledge diffusion. The result is given in Appendix C.

effect, suggesting the outward international technology linkages of Indian industries are still under-developed compared to other countries in our sample.[19]

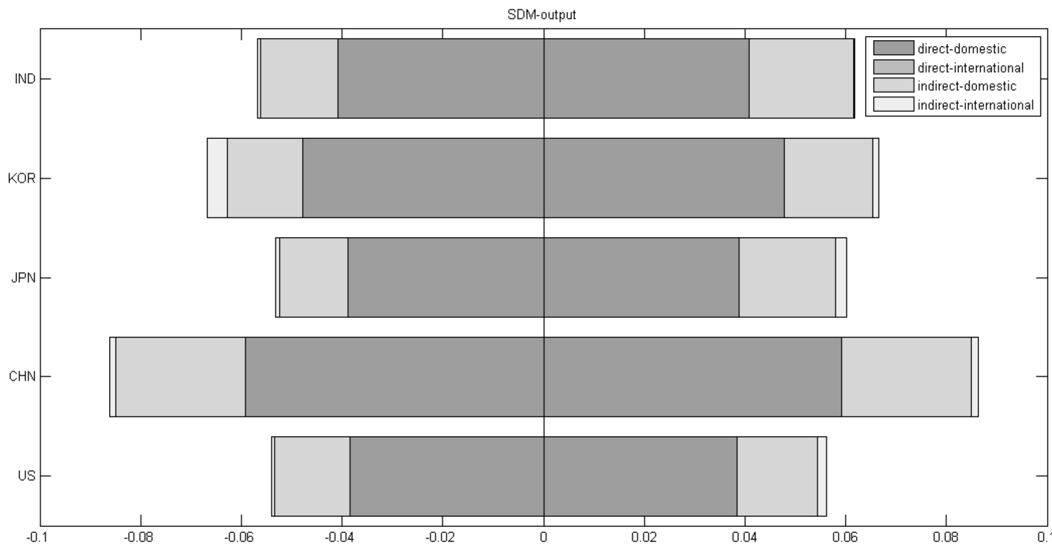

FIGURE 4

Direct and Indirect Effect of Hicks-neutral Technological Change

Figure 5 displays the matrices based on the indirect effects of technical change for each country in our sample. The dots represent the receiving and offering spillovers for each industry. The position on the horizontal axis indicates the indirect effect offered to other industries and the position on vertical axis indicates the indirect effect received from other industries. The sequence number of industry is labeled near the dot.

[19] The international direct effect is negligible since the international feedback part of direct effect is quite small.

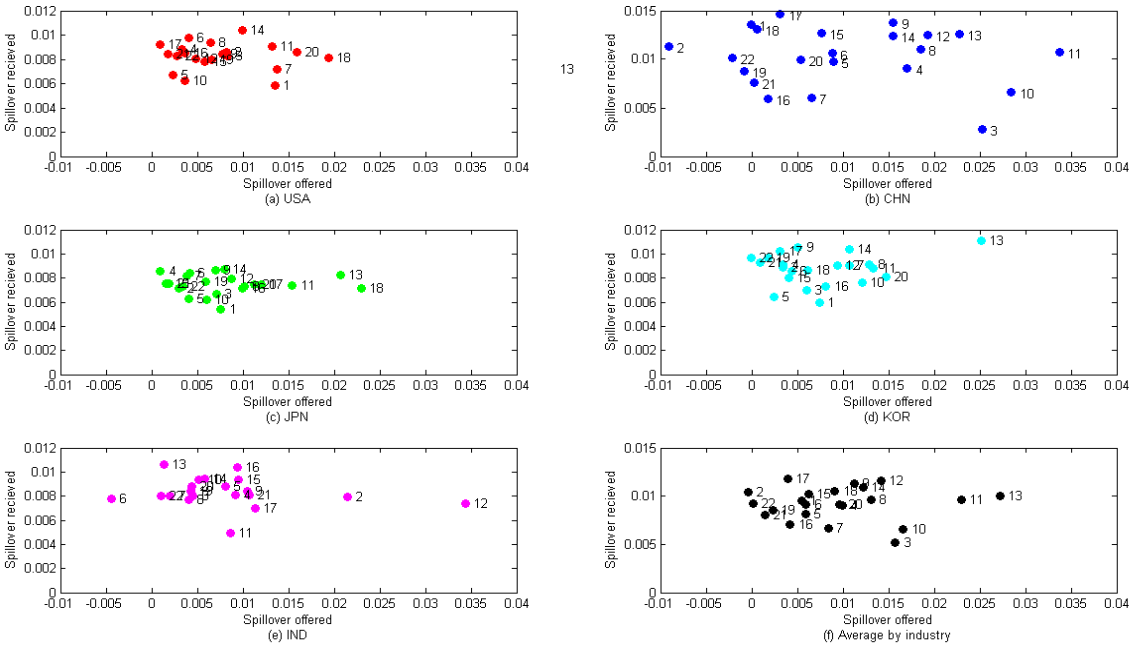

FIGURE 6

Spillover offered and received for all industries

Figure 6 clearly indicates the different distributions of spillovers measured by the direction of spillovers received and offered. The spillover received is measured by average growth weighted by the linkages defined by the spatial weight matrix. The spillover offered is measured by the growth of the industry itself augmented by the linkages with other industries. Thus, the spillover measured by offering is more disperse than the spillover measured by receiving. The top 3 industries with the largest spillovers offered on average are the manufacturing industries Electrical and Optical Equipment (s13), Basic Metals and Fabricated Metal (s11), Machinery and Nec and Recycling (s12), with indirect effects of 0.023, 0.017 and 0.015. The service industry with the most spillovers offered on average is Wholesale and Retail trade (s18), with an indirect effect of 0.012. The industry with the most spillover received on average is Machinery, Nec (s12), with an indirect effect of 0.014. The other industries are relatively concentrated in distribution.

We also measure the direct and indirect effects of time trends in value of gross output from the perspective of the receiving spillover by decomposing the increment of gross output into a direct increment and an indirect increment. From Eq. (6) and Eq. (15b) we have the total increment of gross output, $\Delta Y_{t+1}^{r} = e^{gTot_t^r} Y_t - Y_t$, from the perspective of the receiving spillover. Since there is an interactive influence from the direct and indirect effect, to qualify the explanation from both, we follow the two-polar-averaging decomposition method of Dietzenbacher and Los (1998) to calculate the contributions of each component. The direct and indirect increment of output in 2010 for the US is 320,459 and 126,213 million US dollars respectively, which contributed 72% and 28% of total output increment of the industries in our sample[20]. The industries in China benefit most from the spillovers since the increment of gross output from indirect effect is 177,113 million US dollars, which contributed 28% of total output increment.

TABLE 4

Increment of gross output decomposed by direct and indirect effect
(in million US dollars)

	Direct effect	Indirect effect	Total effect
US	320,459	126,213	446,672
CHN	466,879	177,113	643,992
JPN	145,985	53,314	199,299
KOR	55,523	19,995	75,519

[20] We remove the non-market industries from our sample. These industries in US accounts for 43% of total gross output and this ratio is much smaller than the ratio in other countries. Therefore the total increment of gross output seems relatively smaller than China.

IND	51,531	19,798	71,329

5.4 Productivity level and change for selected industries: electrical and optical equipment

The information and communication technology (ICT) industry is one of the fastest growing industries in the world and highlights the increasingly important role of the global production system in the past 30 years. Jorgenson et al. (2012) note the important role of ICT-producing industries, including software and hardware manufacturing and services, and they found a substantial contribution of these industries to economic growth. Due to the importance of ICT as a main industry in which innovation takes places and provides an engine for long-run growth in an economy, we next examine the Electrical and Optical Equipment industry to show the performance of the ICT industry in the five countries we study and the way in which spillovers are diffused through domestic and international supply chains.

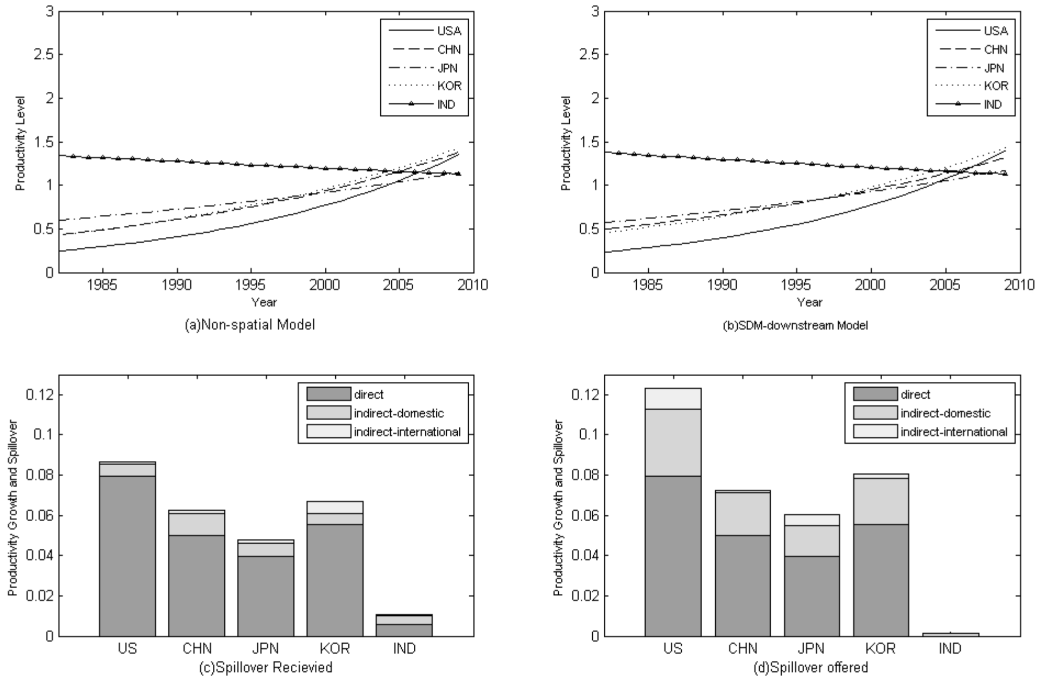

FIGURE 5

Productivity Level, Growth and Spillover of Electrical and Optical Equipment

Productivity change and spillovers in the electrical and optical equipment industry measured in our models are shown in Figure 5. Panel (a) and (b) are the total factor productivity estimates of Electrical and Optical Equipment in each country based on the estimation results of the non-spatial CSSG model and SDM-downstream CSSG model. The estimated productivity levels from the two models are comparable, with an increasing trend for US, China, Korea and Japan and a decreasing trend for India. The direct effect, which represents the technical progress of each industry, suggests that the US, with a growth rate of 6.59%, is the most successful country in the developing ICT industry, although the gross output in that industry in China has soared 30% during this period (by 1,734,075 million US$), while increasing by less than 10% in the US (by 519,011 million US$). The Korean, Chinese, and Japanese annual growth rates were of 4.21%, 3.60% and 2.65%, while productivity in the Indian sector falls during this period.

The gross output of electrical and optical equipment industry in India in 2010 is $72,824 million US$, which is only 4.2% of the gross output in China, suggesting a large gap in scale exists with other countries in our sample.

The technological spillovers offered and received can help us understand the role of an industry in technological diffusion within the global value chain. Panel (c) and (d) of Figure 5 provide more detailed comparisons for productivity growth spillovers from the perspective of receiving and offering. In panel (c), the estimates of spillovers received show that China benefits most from the production network with the indirect effect of 1.26%. However, the domestic indirect effect of China is 1.13%, indicating the spillovers mostly are coming from the domestic industrial linkages within China. The ICT of Korea is the industry that absorbs the largest international spillover with an international indirect effect of 0.59%.

As shown in panel (d), the spillover of productivity growth offered by US Electrical and Optical Equipment is 4.39%, which is the highest of all industries in our sample, suggesting that the US ICT industry is in the position of an innovation hub in the global value chain. Korea, China and Japan follow in descending order with indirect effects of 2.51%, 2.28% and 2.07%. Compared with the sample average indirect effect of 0.86%, ICT in these countries seems to be an important engine for regional economic development. The Electrical and Optical Equipment sector in the US also has the highest international growth spillover at 1.07%, followed by Japan, Korea and China at 0.56%, 0.24% and 0.15%, respectively. Therefore, although China could be thought of as representative of a developing country while OECD member Korea, representing NIEs, have the fastest growth measured by output of ICT, the developed countries such as the US and Japan still have the largest contributors measured by the productivity growth spillover offered.

6 Conclusion

In this paper, we develop a growth model which allows for technological interdependence on an industry-level with heterogeneous productivity growth in the GVCs. The World Input-output tables are used to construct the spatial weight matrix, which describes the spatial linkages between any pair of industries. We also propose a method to measure technology spillovers by each factor input as well as Hicks-neutral technical change. These spillovers are then decomposed into a domestic and international effect by separating out the local multipliers from the global multiplier of the spatial effect. We estimate the model using non-spatial, SAR and SDM specifications.

The SDM specification is preferred over the SAR specification based on standard statistical criteria. Results from the SDM-downstream model suggest that the internal elasticities of factor inputs measured by direct effects are comparable to those from the non-spatial model. However, with the spatial model we are able to estimate the indirect effect, and we found negative external elasticities for capital and labor input and a positive external elasticity for the intermediate input. The international indirect effect accounts for about 6.5% of the external elasticity for each factor. The Domar-weighted direct technical change growth rate for China, Korea, India, the US and Japan is estimated to be 2.64%, 2.04%, 1.75%, 1.36% and 1.33%, respectively. The spillovers received account for 27% to 31% of their total technological growth and its international portion varies across the countries, with the highest, Korea, at 22% and lowest, India, at 3.5%. The developed countries such as US and Japan are the highest in net international spillovers offered. The important Electrical and Optical Equipment sector of the US has the fastest productivity growth and offers the most spillovers in our sample, although China has predominance in scale in this industry.

Our paper also speaks to anxieties felt by both rich and poor countries as trade and supply chains become increasingly global. Developed countries worry that technology is imitated by developing countries, which may shake their dominate position in global value chain and induce a series of problems such as industry hollowing-out and unemployment. Developing countries worry that they are locked in low value added activities of GVCs and have no limited options to be engaged in higher value-added activities such as design, R&D and marketing. Our results suggest that China, as a representative of a developing country, has experienced high productivity growth in the globalization, but the spillovers received are mostly from domestic linkages, which may benefit from the great varieties of industrial category in China. The international spillovers are more likely to occur between countries at similar stages of development. Further research oriented towards developing a spatial weight matrix that may better depict the network of knowledge transfers among industries and estimation techniques for time-varying social-economic spatial weight matrix with the problem of endogeneity resolved is under way. These may allow us to better uncover the mechanism of technology interaction among countries and sectors within them and provide more accurate measurements of the dynamic spillover process.

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Appendix

A. Elasticity analysis for output with respect to capital, intermediates, and labor

In the SAR model from Eq.12:

$$y = \alpha(I - \rho W_N \otimes I_T)^{-1} k + \beta(I - \rho W_N \otimes I_T)^{-1} m + (I - \rho W_N \otimes I_T)^{-1}\big(\omega_0 + r\delta_g + qU + V\big) \quad (20)$$

We have

$$lnY - lnL = \alpha(I - \rho W_N \otimes I_T)^{-1}(lnK - lnL) + \beta(I - \rho W_N \otimes I_T)^{-1}(lnM - lnL) + (I - \rho W_N \otimes I_T)^{-1}\big(\omega_0 + r\delta_g + qU + V\big) \quad (A.1)$$

Then lnY can be expressed as follows

$$lnY = \alpha(I - \rho W_N \otimes I_T)^{-1} lnK + \beta(I - \rho W_N \otimes I_T)^{-1} lnM + (\gamma I - \rho W_N \otimes I_T)(I - \rho W_N \otimes I_T)^{-1} lnL + (I - \rho W_N \otimes I_T)^{-1}\big(\omega_0 + r\delta_g + qU + V\big) \quad (A.2)$$

Then sum the elasticities of the Output to Capital intermediate and Labor

$$E_K + E_M + E_L = \alpha(I - \rho W_N \otimes I_T)^{-1} + \beta(I - \rho W_N \otimes I_T)^{-1} + (I - \alpha I - \beta I - \rho W_N \otimes I_T)(I - \rho W_N \otimes I_T)^{-1} = (I - \rho W_N \otimes I_T)(I - \rho W_N \otimes I_T)^{-1} = I \quad (A.3)$$

$$E_L = (I - \alpha I - \beta I - \rho W_N \otimes I_T)(I - \rho W_N \otimes I_T)^{-1} = I - (\alpha + \beta)(I - \rho W_N \otimes I_T)^{-1} \quad (A.4)$$

The constant return to scale assumptions still hold to the industries as an aggregate in SAR model, but not hold for individual industries if the effects from the neighbor industries were considered.

In the SDM model from Eq.13:

$$y = (I - \rho W_N \otimes I_T)^{-1}[\alpha + (\phi - \rho\alpha) W_N \otimes I_T]k + (I - \rho W_N \otimes I_T)^{-1}[\beta + (\varphi - \rho\beta) W_N \otimes I_T]m$$
$$+ (I - \rho W_N \otimes I_T)^{-1}\left(\omega_0 + r\delta_g + qU + V\right) \qquad \text{(A.5)}$$

We have

$$lnY - lnL = (I - \rho W_N \otimes I_T)^{-1}[\alpha I + (\phi - \rho\alpha) W_N \otimes I_T](lnK - lnL) + (I - \rho W_N \otimes I_T)^{-1}[\beta I +$$
$$(\varphi - \rho\beta) W_N \otimes I_T](lnM - lnL) + (I - \rho W_N \otimes I_T)^{-1}\left(\omega_0 + r\delta_g + qU + V\right) \qquad \text{(A.6)}$$

Then we can get the expression of lnY

$$lnY =$$
$$(I - \rho W_N \otimes I_T)^{-1}[\alpha I + (\phi - \rho\alpha) W_N \otimes I_T]lnK + (I - \rho W_N \otimes I_T)^{-1}[\beta I + (\varphi - \rho\beta) W_N \otimes I_T]lnM +$$
$$[\gamma - (\phi + \varphi) W_N (I - \rho W_N \otimes I_T)^{-1}]lnL + (I - \rho W_N \otimes I_T)^{-1}\left(\omega_0 + r\delta_g + qU + V\right) \qquad \text{(A.7)}$$

Then summing the elasticities of the Output to capital intermediate and labor we can still get the constant return to scale result.

$$E_K + E_M + E_L = (I - \rho W_N \otimes I_T)^{-1}[\alpha I + (\phi - \rho\alpha) W_N \otimes I_T] + (I - \rho W_N \otimes I_T)^{-1}[\beta I + (\varphi -$$
$$\rho\beta) W_N \otimes I_T] + (I - \rho W_N \otimes I_T)^{-1}[\gamma I + (-\phi - \varphi + \rho\gamma) W_N \otimes I_T] = [\alpha I + (\phi - \rho\alpha) W_N \otimes I_T + \beta I +$$
$$(\varphi - \rho\beta) W_N \otimes I_T + \gamma I - \rho\gamma W_N \otimes I_T) - (\phi + \varphi) W_N \otimes I_T](I - \rho W_N \otimes I_T)^{-1}$$

$$= [(\alpha + \beta + \gamma)I + (\phi - \rho\alpha + \varphi - \rho\beta - \rho\gamma - \phi - \varphi)W_N \otimes I_T](I - \rho W_N \otimes I_T)^{-1} =$$

$$[I - \rho W_N \otimes I_T](I - \rho W_N \otimes I_T)^{-1} = I \qquad \text{(A.8)}$$

B. Detailed derivation of estimation procedure

The Quasi-Maximum Likelihood Estimator for ρ and its implementation are developed in the following way. Let $\psi = (\beta, \gamma, \rho, \sigma_v^2)'$. The log-likelihood function of Eq. (7) is:

$$\log L(\psi, \delta_i; y) = -\frac{NT}{2}\log(2\pi\sigma_v^2) + T\log|I_N - \rho W| - \frac{1}{2\sigma_v^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N}w_{ij}y_{jt} - X'_{it}\beta - Z'_i\gamma - R'_t\delta_i\right)^2, \qquad \text{(B.1)}$$

The first order condition of maximizing Eq. (B.1) with respect to δ_i is

$$\frac{\partial \log L}{\partial \delta_i} = \frac{1}{\sigma_v^2}\sum_{i=1}^{N}\sum_{t=1}^{T}R_t\left(y_{it} - \rho\sum_{j=1}^{N}w_{ij}y_{jt} - X'_{it}\beta - Z'_i\gamma - R'_t\delta_i\right) = 0. \qquad \text{(B.2)}$$

By solving for (B.2), we can obtain

$$\hat{\delta}_i = (R_t R'_t)^{-1}R_t\left(y_{it} - \rho\sum_{j=1}^{N}w_{ij}y_{jt} - X'_{it}\beta - Z'_i\gamma\right). \qquad \text{(B.3)}$$

Substituting (B.3) into the log-likelihood function (B.1), we obtain the concentrated likelihood function

$$\log L(y; \beta, \rho, \sigma_v^2) = -\frac{NT}{2}\log(2\pi\sigma_v^2) + T\log|I_N - \rho W| - \frac{1}{2\sigma_v^2}\tilde{V}'\tilde{V}, \qquad \text{(B.4)}$$

where $\tilde{V} = M_Q y - \rho M_Q (W_N \otimes I_T) y - M_Q X\beta$, and $M_Q = I_{NT} - Q(Q'Q)^{-1}Q'$.

Within Estimator

Assuming that $T \geq L$, the projections onto the column space of Q and the null space of Q are denoted by $P_Q = Q(Q'^{-1}Q')$ and $M_Q = I_{NT} - P_Q$, respectively[21]. Suppose that the true value of ρ is known, and is ρ^*. Pre-multiplying by M_Q, we have the within-transformed model

$$M_Q y = \rho^* M_Q (W_N \otimes I_T) y + M_Q X \beta + \tilde{V}.$$

(B.5)

Estimates of $\beta(\rho^*)$ and $\sigma_v^2(\rho^*)$ are derived by

$$\hat{\beta}_W(\rho^*) = (X'M_Q X)^{-1} X'M_Q (y - \rho^* (W_N \otimes I_T) y),$$
$$\hat{\sigma}_v^2(\rho^*) = \frac{1}{N(T-L)-K} e(\rho^*)'^*),$$

(B.6-B.7)

respectively, where $e(\rho^*) = y - \rho^* (W_N \otimes I_T) y - X \hat{\beta}_W(\rho^*)$. By substituting the closed form solutions for the parameters $\beta(\rho^*)$ and $\sigma_v^2(\rho^*)$ into Eq. (B.4), we can concentrate out β and σ_v^2, and the concentrated log-likelihood function with single parameter ρ takes the form:

$$\log L(y;\rho) = C - \frac{NT}{2} \log\left[e(\rho)'e(\rho)\right] + T \log|I_N - \rho W|,$$

(B.8)

[21] Q needs to be a full column rank matrix for estimation of the individual δ_i ' s .

where C is a constant term that is not a function of ρ. By maximizing the concentrated log-likelihood function Eq. (B.8) with respect to ρ, we can obtain the optimal solution for ρ. Even if there is no closed-form solution for ρ, we can easily find a numerical solution because the equation is concave in ρ. Finally, the estimators for β and σ^2 can be calculated by plugging in $\rho^* = \hat{\rho}$ into Eq. (B.6) and Eq. (B.7).

The asymptotic variance-covariance matrix of parameters (β, ρ, σ^2) is given by:

$$Asy.Var(\beta, \rho, \sigma_v^2) = \begin{bmatrix} \frac{1}{\sigma_v^2}\tilde{X}'\tilde{X} & \frac{1}{\sigma_v^2}\tilde{X}'(W^* \otimes I_T)\tilde{X}\beta & \boldsymbol{0} \\ - & T \cdot tr(W^*W^* + W^{*'}W^*) + \frac{1}{\sigma_v^2}\beta'\tilde{X}'(W^{*'}W^* \otimes I_T)\tilde{X}\beta & \frac{T}{\sigma_v^2}tr(W^*) \\ - & - & \frac{NT}{2\sigma_v^4} \end{bmatrix}^{-1}, \quad \text{(B.9)}$$

where $\tilde{X} = M_Q X$ and $W^* = W(I_N - \rho W)^{-1}$.

Generalized least squares estimator

Alternatively, we can estimate Eq. (7) by generalized least squares (GLS). Denote the variance-covariance matrix of the composite error $\varepsilon = QU + V$ as $\mathrm{cov}(\varepsilon) = \Omega$. The GLS estimator is the SAR estimator applied to the following transformed equation:

$$\begin{aligned} \sigma_v\Omega^{-1/2}y = \rho\sigma_v\Omega^{-1/2}(W_N \otimes I_T)y + \sigma_v\Omega^{-1/2}X\beta + \sigma_v\Omega^{-1/2}\boldsymbol{Z}\gamma \\ + \sigma_v\Omega^{-1/2}\boldsymbol{R}\delta_0 + \sigma_v\Omega^{-1/2}\varepsilon, \end{aligned} \quad \text{(B.10)}$$

where $\varepsilon = QU + V$, $\Omega = \mathrm{cov}(\varepsilon) = \sigma_v^2 I_{NT} + Q(I_N \otimes \Delta)Q'$. The estimation procedure for Eq. (B.10) is comparable to the procedure for within-estimation. Let $\eta = (\beta, \gamma, \delta_0)$.

Assuming we know the true value of $\rho = \rho^*$, the GLS estimators of $\eta(\rho^*)$ are

$$\begin{aligned}\hat{\eta}_G(\rho^*) &= [(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}(X,\boldsymbol{Z},\boldsymbol{R})]^{-1}(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}(y-\rho^*(W_N \otimes I_T)y) \\ &= [(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}(X,\boldsymbol{Z},\boldsymbol{R})]^{-1}(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}y \\ &\quad -\rho^*[(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}(X,\boldsymbol{Z},\boldsymbol{R})]^{-1}(X,\boldsymbol{Z},\boldsymbol{R})^{'-1}(W_N \otimes I_T)y.\end{aligned} \tag{B.11}$$

Hence, the GLS estimators of η can be represented as a difference of OLS estimators of regressing $\widehat{y}$ on $(\widehat{X},\widehat{\boldsymbol{Z}},\widehat{\boldsymbol{R}})$ and regressing $\widehat{(W_N \otimes I_T)y}$ on $(\widehat{X},\widehat{\boldsymbol{Z}},\widehat{\boldsymbol{R}})$ pre-multiplied by the spatial autoregressive coefficient ρ^*, where tilde represents GLS transformation. Ω then can be estimated by:

$$\hat{\Omega}(\rho^*) = \hat{\sigma}_v^2 I_{NT} + Q(I_N \otimes \hat{\Delta}(\rho^*))Q'. \tag{B.12}$$

Following Cornwell, et al. (1990), Δ can be estimated as

$$\hat{\Delta}(\rho^*) = \frac{1}{N}\sum_{i=1}^{N}\Big[(R^{'-1}R'e_i e_i' R(R^{'-1} - \hat{\sigma}_v^2(R^{'-1}))\Big], \tag{B.13}$$

where $e_i = M_R y_i - \rho_i^* M_R (W_N \otimes I_T) y_i - \rho_i^* M_R X_i \hat{\beta}_W$, which represents the IV residuals for individual i, and $M_R = \boldsymbol{R}\left(\boldsymbol{R}^{'-1}\boldsymbol{R}'\right)$ is the projection onto the column space of $\boldsymbol{R}$.

Consider next the likelihood function of Eq. (B.10). Since $\sigma_v \Omega^{-1/2}\varepsilon$ has mean zero and variance σ_v^2, the likelihood function can be written in the form of

$$\log L(\eta,\rho;y) = -\frac{NT}{2}\log(2\pi\sigma_v^2) + T\log|I_N - \rho W| - \frac{1}{2}\varepsilon^{'-1}\varepsilon, \tag{B.14}$$

where $\varepsilon = y - \rho(W_N \otimes I_T)y - X\beta - \boldsymbol{Z}\gamma - \boldsymbol{R}\delta_0$. Substitution of Eq. (B.11) and Eq. (B.12) into Eq. (B.14) gives the concentrated likelihood function:

$$\log L(\rho; y) = C - \frac{NT}{2}\log\left[e(\rho)'e(\rho)\right] + T\log|I_N - \rho W|, \tag{B.15}$$

where

$$e(\rho) = \hat{\sigma}_v\hat{\Omega}(\rho)^{-1/2}y - \rho\hat{\sigma}_v\hat{\Omega}(\rho)^{-1/2}(W_N \otimes I_T)y - \hat{\sigma}_v\hat{\Omega}(\rho)^{-1/2}X\hat{\beta} - \hat{\sigma}_v\hat{\Omega}(\rho)^{-1/2}\boldsymbol{Z}\hat{\gamma} - \hat{\sigma}_v\hat{\Omega}(\rho)^{-1/2}\boldsymbol{R}\hat{\delta}_0 \ , \tag{B.16}$$

and where C is a constant term that is not a function of ρ . Finally, as is the case of the within estimator, we can obtain the estimators for η and Ω using the estimate of ρ from Eq. (B.15).

Implementation of this estimator requires that we combine the procedure suggested by Elhorst (2014) and a typical two-stage approach of Feasible Generalized Least Squares (FGLS). The implementation consists of the following steps.

[Within Estimator]

From Eq. (B.6) it can be shown that $\hat{\beta}_W = b_0 - \rho^* b_1$, where b_0 and b_1 are the OLS estimators from regressing $M_Q y$ and $M_Q(W_N \otimes I_T)y$ on $M_Q X$, respectively. Similarly, the estimated residuals from Eq. (B.5), $e(\rho^*)$, can be expressed as $e(\rho^*) = e_0 - \rho^* e_1$, where e_0 and e_1 are the associated OLS residuals based on b_0 and b_1, respectively. Hence the first step is obtaining b_0, b_1, e_0, and e_1 . Second, we maximize Eq. (B.8) with respect to ρ after replacing $e(\rho) = e_0 - \rho e_1$, i.e.,

$$\max_{\rho} \log L(y \mid \rho) = C - \frac{NT}{2}\log\left[(e_0 - \rho e_1)'(e_0 - \rho e_1)\right] + T\log|I_N - \rho W|.$$

Third, replacing $\rho^* = \hat{\rho}$ in Eq. (B.6) and (B.7), gives the within estimator $\hat{\beta}_W$ and the estimated variance $\hat{\sigma}^2$. Finally, the asymptotic variance-covariance matrix of the parameters $(\hat{\beta}_W, \hat{\rho}, \hat{\sigma}_v)$ can be calculated by Eq. (B.9).

[GLS Estimator]

Unlike the within estimator case, we are unable to find the separate OLS estimators of regressing $\sigma_v \Omega^{-1/2} y$ and $\sigma_v \Omega^{-1/2}(W_N \otimes I_T) y$ on $\sigma_v \Omega^{-1/2}(X, \boldsymbol{Z}, \boldsymbol{R})$ in advance of having $\hat{\rho}$, even if Eq. (B.11) is expressed as a subtraction of two terms. This is because the feasible Ω is obtainable only after we have a value for ρ. Instead of following the steps of within estimator, we can obtain $\hat{\rho}$ by simply maximizing the concentrated log-likelihood function (B.15). Once we have an estimate $\hat{\rho}$, Eq. (B.13), Eq. (B.12), and Eq. (B.11) give $\Delta(\hat{\rho})$, $\Omega\hat{\rho}$, and $\eta_G(\hat{\rho})$.

C. Estimation with spatial weight matrix based on the 2010 input-output tables

TABLE 5

Estimate of SDM Production Function with spatial weight matrix of 2010

	(1)	(2)
	SDM-downstream	
	CSSW	CSSG
Lnk	.103***	.100***
	(.011)	(.011)
Lnm	.569***	.582***

	(.011)	(.010)
W•lnk	-.027**	-.037*
	(.023)	(.022)
W•lnm	-.108***	-.057*
	(.034)	(.031)
Country-Dummy	No	Yes
Intercept		-.001
		(.044)
Time		.003**
		(.002)
W•lny(ρ)	.344***	.305***
	(.025)	(.025)
σ_v^2	.009	.009
R^2	.823	.829
Adjusted R^2	.808	.814
LL	3023.667	2934.214

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

TABLE 6

Elasticity of input factors by estimation with spatial weight matrix of 2010

SDM-downstream		Internal		External		Total	
		Elasticity	asy.t-stat	Elasticity	asy.t-stat	Elasticity	asy.t-stat
overall	Capital	0.103***	9.114	0.051***	3.078	0.153***	6.858
	Intermediate	0.590***	58.377	0.212***	6.181	0.802***	21.138
	Labor	0.302	-	-0.244	-	0.058	-
	Capital	0.103***	9.114	-0.046***	3.089	0.148***	7.091

domestic	Intermediate	0.590***	58.387	0.191***	6.300	0.782***	22.871
	Labor	0.302	-	-0.220	-	0.082	-
	Capital	0.000***	2.812	-0.005**	2.963	-0.005***	2.963
international	Intermediate	0.000***	4.429	0.021***	5.238	0.021***	5.235
	Labor	0.000	-	-0.024	-	0.024	-

Notes: Significant at: *5, * *1 and * * * 0.1 percent; Standard error in parentheses.

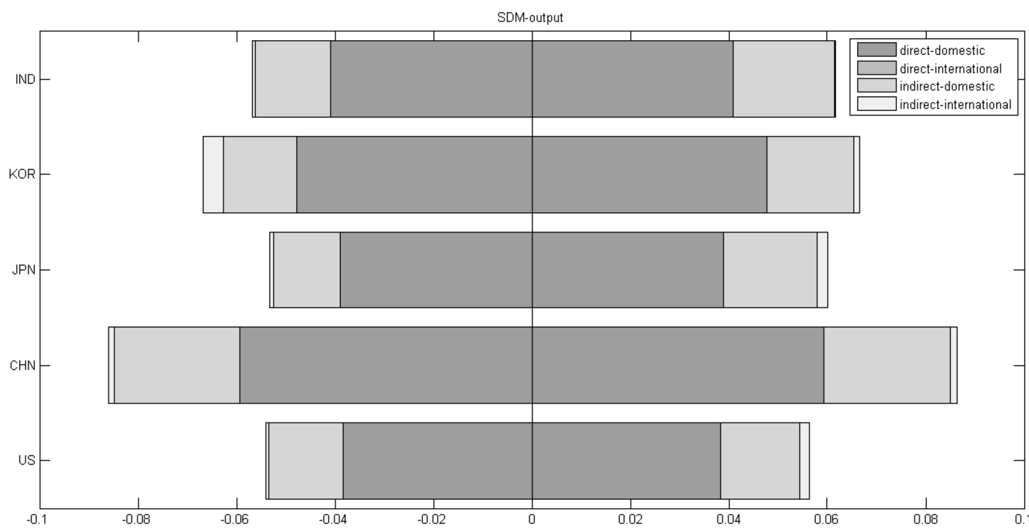

FIGURE 7

Direct and Indirect Effect of Hicks-neutral Technological Change with spatial weight

D. Aggregate productivity growth of each country with different weights

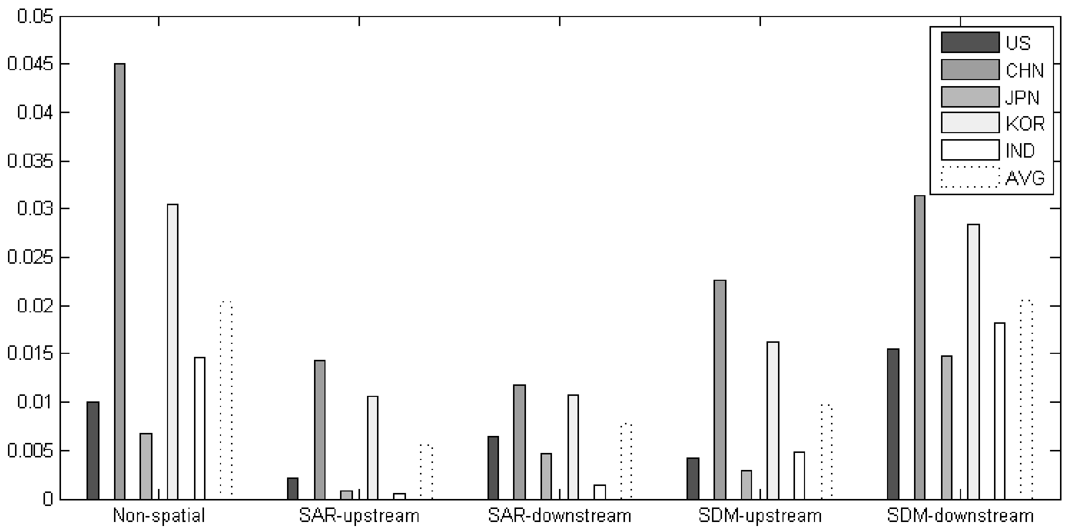

FIGURE 8

Aggregate productivity growth with Domar weights on open-economy assumption

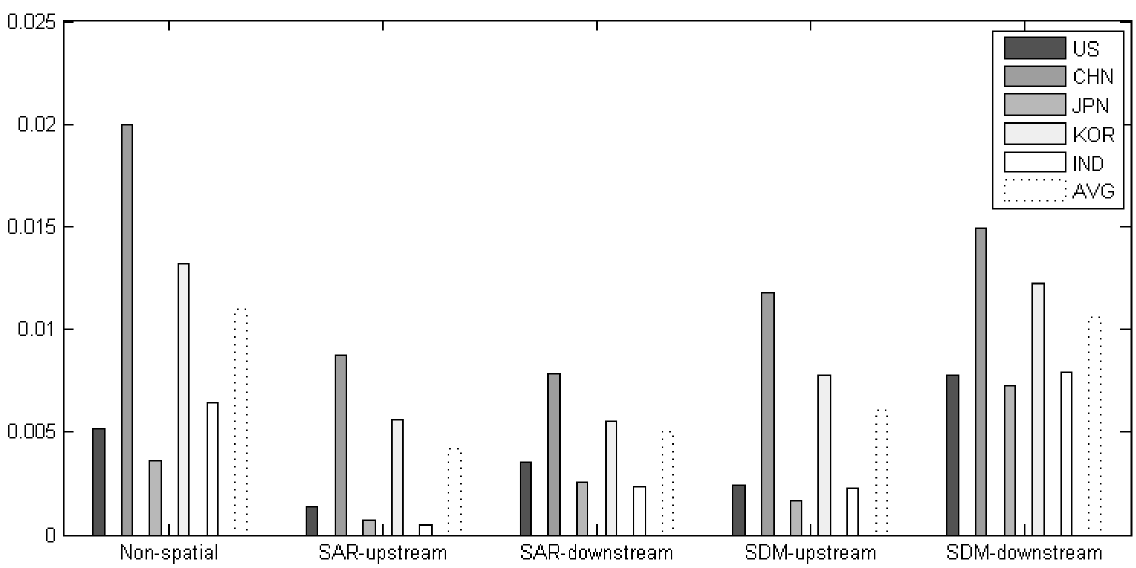

FIGURE 9

Gross output weighted average productivity growth of each country