Industry-Specific Productivity and Spatial Spillovers through input-output linkages:

Evidence from Asia-Pacific Value Chain

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Abstract

Global value chains (GVCs) promote the diffusion of knowledge and technology among the participants in the international production network and accelerate knowledge sharing and vertical specialization. These technological spillovers are main drivers of technological progress and the long-term growth of participating countries. This paper develops an empirical growth model that combines spatial spillovers and productivity growth heterogeneity at the industry-level. We exploit the GVCs' linkages from inter-country input-output tables to describe the spatial interdependencies in technology. The spillover effects from capital deepening, intermediate deepening, and technical change are identified using a spatial econometric specification. We use local Leontief matrices to decompose these effects into the domestic value chain spillovers transmitted within a country and the international value chain spillovers transferred across the borders. Our empirical results with the industry-level data of five Asia-Pacific countries find that ignoring the spatial interactions leads to an overestimation of China's productivity growth, and underestimation of productivity growth in developed countries such as the US and Japan. The spillover effects of capital and intermediate inputs per capita are found to be significantly positive. Domar-weighted direct technical change growth rates for China, Korea, India, Japan and US are estimated to be 5.05%, 4.06%, 3.35%, 3.32% and 3.30%. and the spillovers received account for 31% to 34% of their total technological growth.

The estimated international spillovers offered suggest that US is the main contributor of international knowledge diffusion, and the Electrical and Optical Equipment sector of the US has the fastest productivity growth and offers the most spillovers. These finding provide a better understanding of how technical changes are distributed and diffused within the GVCs network.

Keywords: Industry-specific productivity, Spatial panel model, Technological spillovers, Global value chain, Asia-Pacific trade, World KLEMS database

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

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Highlights

- This study analyzes the distribution and diffusion of industry-level technical change within the GVCs network.
- A spatial production model with heterogeneity in technical progress and spatial interdependency is developed.
- Capital-deepening and intermediate deepening in neighbor industries have positive spillover effects.
- The spillover effect occupies a considerable proportion of the impact of Hicks-neutral technical change.
- These results have implications for countries in their choice of strategies to participant in the global value chain.

1 Introduction

Over the past two decades, the world economy has evolved rapidly and the network structure of 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.[1]. 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 substantial and increasing. 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 global supply chain. 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

[1] The UNSD Commodity Trade (UN Comtrade) database.

estimate domestic and foreign components in export. Acemoglu et 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. (2014) and Timmer and Ye (2018) 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 others are not, during the rapid development in GVCs.

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 main driver of technological progress and thus long-term growth (Lucas and Moll, 2014; Acemoglu and Cao, 2015; Bondarev and Krysiakb, 2021)

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; Demir and Duan, 2018) 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. (2018) 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 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. Another strand of literatures emphasizes the spillover effect within the cross-sectional network of industries through input-output linkages, see for example Acemoglu et al. (2012) who argue that idiosyncratic shocks may lead to aggregate fluctuations through inter-sectoral input–output linkages. Atalay (2017) suggests that industry-specific shocks account for nearly two-thirds of the volatility of aggregate output. Autor and Salomons (2018) consider the weighted sum of TFP growth in supplier and customer industries as indirect effect, and the weights are obtained from the input-output coefficients from the World Input-Output Database (WIOD). 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 that allows productivity growth to vary over 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.

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) to calculate 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 Leontief 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. 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 Leontief 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. Appendices A-F contain more detailed discussions of estimation procedures, additional results, specification test results for the alternative models we consider in our analyses, and a simulation of how the COVID-19 pandemic outbreak would impact trade based on our spatial model under different World Trade Organization scenarios.

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:

$$Y_{it} = A_{it} {K_{it}}^{\alpha} {M_{it}}^{\beta} {L_{it}}^{\gamma}, \;\; i = 1, \cdots, N, \;\; t = 1, \cdots, T, \tag{1}$$

where Y_{it} is total output, K_{it}, M_{it} and L_{it} are the capital, intermediate, and labor inputs, and $\alpha + \beta + \gamma = 1$. A_{it} is the aggregate level of productivity, which differs among industries and time periods.

The productivity level A_{it} is specified as

$$A_{it} = e^{R_t' \delta_i}, \tag{2}$$

where R_t is an $L \times 1$ component that affects each sector (in our empirical model we utilize a constant and a time trend[2] so that *L=2*) and δ_i is an $L \times 1$ vector of coefficients that depend on *i*. Contained

[2] Our use of time as a proxy for technical change is driven by a lack of better proxies for innovation at the sector level for the countries in Asian KLEMS sample. However, our approach can be used with more precise measures of innovation. For example, Kalaitzi and Chamberlain (2020) assume that total factor productivity can be expressed as a function of merchandise exports, imports of goods and services while Hallonsten and Ziesemer (2019) specify the growth rate of technology or total factor productivity by the linear function of *t* but also considered the public capital (B) in the

in the constant is the sector-specific initial technology state. This is the Solow model (Solow, 1956; Swan, 1956; Ertur and Koch, 2007) where the assumption of identical technical progress in all industries is lifted by allowing for an industry-specific time trend. We can then write the non-spatial production function per worker as:

$$y_{it} = A_{it} k_{it}^{\alpha} m_{it}^{\beta} = e^{R_t' \delta_i} k_{it}^{\alpha} m_{it}^{\beta}, \tag{3}$$

where $y_{it} = Y_{it}/L_{it}$, $k_{it} = K_{it}/L_{it}$, $m_{it} = M_{it}/L_{it}$.

The coefficient δ_i is expressed in terms of deviations (u_i) from its mean δ_g and we interpret $R_t'\delta_g$ as a global constant and technology growth term and $R_t' u_i$ as a sector-specific initial technology state and technology growth term. As we have indicated, the technology growth term is proxied by a time trend. Taking the logarithm of Eq. (3), we have:

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

We assume that the u_i are *iid* zero mean random variables with covariance matrix Δ, and v_{it} is the usual *iid* zero mean disturbance term with variance σ_v^2. Of course, if u_i is constant, then the production function can be written in the usual form and Eq. (4) reduces to the standard panel data model with a time trend.

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production model. Heshmati and Rashidghalam (2020) allow TFP growth to be driven by unobservable time trend induced technical change, scale economies and an observable technology shifter whose components include development infrastructure measures, research and development expenditure, hi-tech exports, patent applications, and levels of human development.

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 (2007) 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 while at the same time allowing the industry to absorb knowledge diffusion from its neighbors. The productivity growth originating in supplier industries may bring higher quality intermediates and know-how to downstream industries. Similarly, the productivity growth occurring in customer industries may increase the requirement of intermediate quality and thus stimulate learning and capability building to upstream industries[3]. We start with assuming 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 expressed as

$$A_{it} = e^{R_t'\delta_i} \prod_{j\neq i}^{N} y_{jt}^{\rho w} \tag{5}$$

and this leads to the following per worker production function:

$$y_i(t) = e^{R_t'\delta_i} \prod\nolimits_{j\neq i}^{N} y_j(t)^{\rho w_{ij}} k_i(t)^{\alpha} m_i(t)^{\beta} exp(v_{it}). \tag{6}$$

Taking logarithms of the expression, we obtain the Spatial Autoregressive (SAR) model

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

[3] We note that this mechanism is different from the shock propagation through the fluctuation in intermediate input that leads to the change in output, since that part of effect is considered in the input variable of *m* in our model.

which we can write more compactly as

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

where y, k, m and V are $NT \times 1$ vectors, W_N is N×N matrix composed by w_{ij} with diagonal elements set to 0, ι_N is N dimensional vector of ones, $R = (R_1, R_2, \cdots, R_T)'$, $r = \iota_N \otimes R$, $Q = diag(\iota_N) \otimes R$ 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 other sectors' labor productivity, but by the other sectors' technology A_{jt}, capital-labor ratio k_{it}, and intermediate-labor ratio m_{it}. The capital deepening in supplier or customer industries may increase aggregate social capital and thus accumulate knowledge and provide productivity improvement to the industry in question, which is in accordance with the Arrow-Romer's physical capital externalities (Arrow,1962; Romer, 1986). Analogously, the increase in intermediate input per capita in supplier or customer industries may also be beneficial to productivity growth because of the deepening in division and specialization among industries (denoted as intermediate deepening). Thus the function describing the technology of industry *i* depends on three components. First, some portion of technical progress is exogenous and heterogeneous among industries : $\delta_g R_t{}' + R_t{}' u_i + v_{it}$. Second, each industry's technology is interdependent with its neighbors, dependent on the relative connectivity with its neighbors and these neighbors' technical progress: $\rho \sum_{j=1}^{N} w_{ij} \ln A_{jt}$. Third, the technology of industry *i* will be increasing with the ratio of capital and intermediates to labor: $\phi \ln k_{it} + \varphi \ln m_{it}$, and this process also increases the level of technology for all industries by raising the aggregate level of capital deepening or intermediate deepening through knowledge spillovers. This leads to the following expression for (the log of) technology:

$$\ln A_{it} = \rho \sum_{j=1}^{N} w_{ij} \ln A_{jt} + \phi \ln k_{it} + \varphi \ln m_{it} + \delta_g R_t{}' + R_t{}' u_i + v_{it}. \tag{9}$$

Then solving A_{it} and rewriting A_{it} in matrix form we have:

$$A = (I - \rho W_N \otimes I_T)^{-1} \big(\phi k + \varphi m + \delta_g r + QU + V\big). \tag{10}$$

Replacing this expression in the production function and multiplying both sides of the equation by $(I - \rho W_N \otimes I_T)$, we obtain the production function in a Spatial Durbin form[4]:

$$\begin{aligned} y &= (I - \rho W_N \otimes I_T)^{-1} \big(\phi k + \varphi m + \delta_g r + QU + V\big) + \alpha k + \beta m \\ &= \rho (W_N \otimes I_T) y + \alpha k + \beta m + \delta_g r + QU + V \\ &+ (\phi - \alpha\rho)(W_N \otimes I_T) k + (\varphi - \beta\rho)(W_N \otimes I_T) m. \end{aligned} \tag{11}$$

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):

$$\begin{aligned} y &= \alpha (I - \rho W_N \otimes I_T)^{-1} k + \beta (I - \rho W_N \otimes I_T)^{-1} m \\ &+ (I - \rho W_N \otimes I_T)^{-1} \big(r \delta_g + QU + V\big), \end{aligned} \tag{12}$$

[4] Strictly Eq. (11) 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 $R_t{}' \delta_g$.

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

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

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:

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

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

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 effect 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).

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 $gDir_t$, are 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 $gTot_t^r = gDir_t + gInd_t^r$. 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 and has been observed in both global value chains and regional/local value chains (Charlotte et al, 2021). Suppose there are two countries s and r, with Q_s and Q_r industries, 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[5]:

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

[5] In the equation below, the number of industries in both countries does not have to be equal, i.e. the dimension of W_{ss} does not need to be the same as W_{rr}. Since W_N is not necessarily symmetric, the transpose of W_{sr} is different from W_{rs}.

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 $H_{ss} \equiv (I_s - \rho W_{ss})^{-1}$. 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[6]:

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

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 $\rho G_{sr} W_{rs} H_{ss}$ corresponds

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

to the process of the technology firstly transmitted from country s to country r 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.

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

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

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}, and direct, indirect and total international effects of per-worker capital expressed as ei_k^{Dir}, ei_k^{Ind} and ei_k^{Tot}. 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

The non-spatial model given in Eq. (4) can be estimated via three linear techniques: within (dummy variables), generalized least squares, and efficient instrumental variables if one adopts a modification of the Hausman and Taylor (1981) approach based on selective orthogonality conditions imposed on a subset of the regressors with which the effects (u_i) are uncorrelated. However, when either a SAR or SDM are considered (Eqs. 8 and 11) we need to turn to an alternative estimator. We adopt a variant of the quasi-maximum likelihood estimation (QMLE) procedure discussed in Glass et al. (2016). 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 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. (8) and (11). The spatial parameters of $(\phi - \rho\alpha)$ and $(\phi - \rho\beta)$ 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 parameter estimates of $\alpha, \beta, \gamma, \rho, \phi, \delta_g, \sigma_v^2$ can be found once we have an estimate of $\hat{\rho}$. A more detail discussion of the algorithm is presented in Appendix A and is based on Han (2016).

4 Data

The countries in our sample include the United States, China, Japan, Korea and India, which are the main economies in the Asia & Pacific area[7]. The international production network has rapidly developed among these countries since the 1980's. 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. We extract the output measures of gross output and input measures of capital service, labor service and intermediate input from the KLEMS database, which provides the quantity and price indices data for the United States, Japan, Korea and India. 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. We use 2005 as the base year for the countries in our study.

[7]Although the five countries are important and closely linked economies in the world, our sample setting here implies a restrictive assumption that the knowledge spillovers considered occur primarily among these five countries at the exclusion of other countries in the world. We acknowledge this data limitation issue as a potential future research topic when data covering a broader range of countries is available.

The inter-country input-output data are drawn from the WIOD database[8]. We match and aggregate some of the industries due to differences in the industry classification across the databases of KLEMS, WIOD and CIP, although they are broadly consistent with the ISIC revision 3. The nominal volumes 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[9]. 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

[8] In this data it is assumed that the input mix for domestic and export product in each industry is homogenous.

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

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, Not Elsewhere Classified (NEC)	29
13	Electrical and Optical Equipment	30t33
14	Transport Equipment	34t35
15	Manufacturing NEC and 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. Hulten (1978) suggests that the input-output structure may act as the channel for technology shock transmission among industries. Correlations between intermediate inputs and technology shocks are also discussed in Nishioka and Ripoll (2012). Foster-McGregor et al. (2017) found that R&D spillovers through intermediate inputs are present and economically important. Lee (2020) suggests that importing and exporting in intermediate inputs can be an important conduit for technology spillovers across borders.

We use the inter-industry intermediate flows in the World Input-Output table to construct the spatial weight matrix on an industry level. Then the matrix of the input-output table can reflect the channel of spillovers that comes from producing for the users of the intermediate product, which is consistent with the theory of "learning-by-doing" in the endogenous economic growth literature. The spatial weights matrix is expressed as $W1$ with elements of $w_{ij} = IO_{ij}$ for $\forall i \neq j$, indicating intermediate inputs from industry i to industry j in nominal US dollar values. We can also obtain a symmetric spatial weight matrix by summing the original and transposed matrix of the input-output table, where the matrix represents the channel of spillover that comes from not only producing for downstream users but also absorbing technical know-how embodied in intermediates from upstream suppliers[10]. The spatial weights matrix is expressed as $W2$ with elements of $w_{ij} = w_{ji} = IO_{ij} + IO_{ji}$, $\forall j \neq i$. 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.

[10] Likewise, we can also use the transposed input-output table as the spatial weight matrix to simulate the spillover by using the intermediate from upstream suppliers. The estimations result is almost equal to the result of spatial weight matrix with *W2*.

However, in this paper, we assume that the productivity spillover is dependent on the share weighted sum of the productivity of their intermediate partners[11], 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 $R(t)'\delta_i = \delta_i t$ 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).

5.1 Estimations of Production Functions

In Table 2, we provide non-spatial estimates of the Solow-type production function Eq. (4) of the industries in our selected countries. The dependent variable is the gross-output per capita. All

[11] 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 than big enterprise, although big company may use more products from the same supplier than the small company.

coefficient estimates for the factor inputs are statistically significant. The coefficients of inputs can be interpreted as output elasticities. The elasticity of intermediate input per capita is the largest, while capital per capita is the smallest. We also can estimate the parameters for the time trend of productivity in the random effects model. Year dummy variables are included to address any macro shocks these countries face during the 30 years of the sample period. Hausman-Wu statistic for the time-varying fixed effects v. time-varying random effects specification has a *p*-value of 0.803 and thus we do not reject the time-varying random effects specification for the non-spatial specification. The coefficient on the *Time* variable is about 0.009 which implies the average productivity growth rate of the economy is about 0.9% in this period. This is consistent with the findings of Miyagawa, et al. (2017) and Wu et al. (2017).

TABLE 2

Estimate of Non-spatial Cobb-Douglas Production Function

	(1)	(2)
Variables	Time-Varying FE (T-V FE) Estimates and Standard Errors	Time-Varying RE Estimates (T-V RE) and Standard Errors
lnk(α)	.110***	.108***
	(.012)	(.011)
lnm(β)	.576***	.591***
	(.011)	(.010)
Country-dummy	No	Yes
Year-dummy	Yes	Yes
Intercept		-0.084*

		(.044)
# 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 3 provide estimates of the SAR and SDM specified production functions with spatial spillovers based on Eq. (8) and Eq. (11). 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 0.241 to 0.284 for SAR and 0.320 to 0.378 for SDM. The parameters ϕ and φ, which represent the local spatial relationships of factor inputs, and their standard errors can be calculated based on the expressions in Eq. (11). In the SDM-Downstream model, estimates of ϕ and φ and their standard errors are 0.018 (0.026) and 0.045 (0.038) for the T-V FE specification while they are 0.005 (0.24) and 0.074 (0.36) for the T-V RE specification. In the SDM-Down+Upstream model, parameter estimates and their standard errors are 0.009 (0.031) and 0.063 (0.044) for the T-V FE specification and -0.010 (0.027) and 0.103 (0.041) for the T-V RE specification. Across the different specifications these estimates are relatively small and the first is not significant at usual nominal levels. However, we should note that these parameters in our spatial model represent only a portion of spillovers channeled directly through the spatial correlation in the capital and intermediate inputs. The other part of the input spillovers is channeled through the spatial correlation of output. It is the sum of these two parts that makes up the indirect effect, which is highly significant (Tables 3) and it is this total indirect effect that we are interested in capturing in our model. For a further discussion of these two components that make up the total indirect spillover see LeSage and Pace (2009). Our results suggest that the neighbour's intermediate inputs have a positive effect on the productivity of an industry. The intuitive implication for the role of the inputs is related to the direct and indirect effect that we more fully explain in Section 5.2 below.

TABLE 3

Estimates of SAR and SDM Production Functions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	SAR Estimates and Standard Errors				SDM Estimates and Standard Errors			
	Downstream		Down+Upstream		Downstream		Down+Upstream	
	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE
lnk	.100***	.099***	.097***	.096***	.106***	.103***	.103***	.101***
	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)	(.011)
lnm	.567***	.581***	.564***	.579***	.570***	.584***	.570***	.582***
	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)	(.011)	(.010)
W•lnk					-.022	-.028	-.029	-.042
					(.026)	(.024)	(.031)	(.028)
W•lnm					-.170***	-.112***	-.145***	-.083**
					(.038)	(.037)	(.044)	(.042)
Country-dummy	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*	*No*	*Yes*
Year-dummy	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Intercept		.008		.014		-.029		-.024
		(.043)		(.043)		(.045)		(.046)

Time		.002		.001		.004*		.004*
		(.002)		(.002)		(.002)		(.002)
W•lny(ρ)	.259***	.241***	.284***	.254***	.378***	.320***	.366***	.320***
	(.024)	(.018)	(.024)	(.018)	(.029)	(.029)	(.029)	(.029)
Adjusted R^2	.803	.807	.802	.806	.799	.803	.798	.803
LL	2985.40	2895.15	2992.37	2902.04	2998.95	2906.24	3002.67	2910.89

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

The *intercept* terms estimated with the time-varying RE model are positive in the SAR model and negative in SDM model but insignificantly different from zero. In the SAR model, the coefficients for linear *time trends* for both specifications of spatial weight matrices are small and insignificant from zero. However, in the SDM models, the estimated parameters for the time trend are both 0.004 which is significantly different from zero.

Additional specification tests for correlated random effects and the potential presence of spatial autocorrelation still present in the error term are provided in Appendix D. Results indicate that the time-varying RE model SAR and SDM models cannot be rejected vis-à-vis other specifications we consider, such as the time-varying FE SAR and SDM model as well as Spatial Error models.

In Figure 1 we calculate aggregate productivity growth for the five countries based on the time-varying RE 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[12]. 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 22.18 and 17.71 for the intermediate and output spatial weight matrices, which suggests that the SDM specification is more statistically significant than SAR specification, which in turn implies that there may exist capital and intermediate externalities in the growth process. Therefore, the models with spatial weighted independent variables are the appropriate specification for the samples[13]. Furthermore, we choose the partial Spatial Durbin model with the spatial weight matrix based on bidirectional linkages of upstream and downstream as our baseline model as it yields the highest log likelihood values. We also test for correlated random effects in our SDM specification and find no evidence of such effects at nominal significance levels. Moreover, we have also examined a factor model specification based on the work of Kneip, et al. (2016) to address any

[12] 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 C.

[13] 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.

spatial correlation in the disturbance term. Moran tests of the whitened residuals do not reject the null hypothesis of no spatial effects in the disturbance at nominal significant levels. Results are robust to these additional empirical treatments. Thus, the remainder of our discussion of results is based on the time-varying random effects estimator. The estimated technical change in the SDM-Up+Downstream model suggests that China has the fastest aggregate productivity growth of 1.99%. 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 lower level of TFP growth rates. They are 0.87% and 0.61% in the non-spatial model and 0.97% and 0.92% in the SDM-Up+Downstream model.

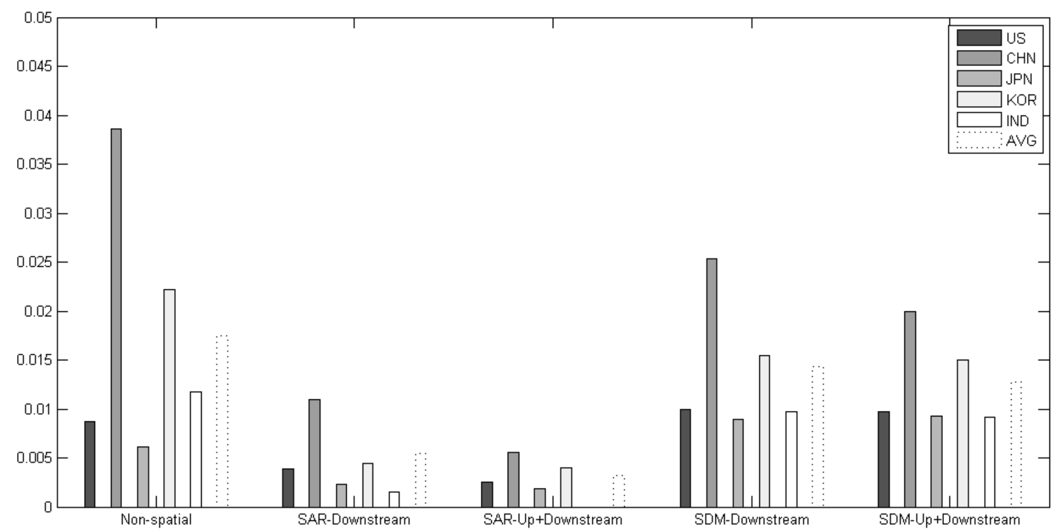
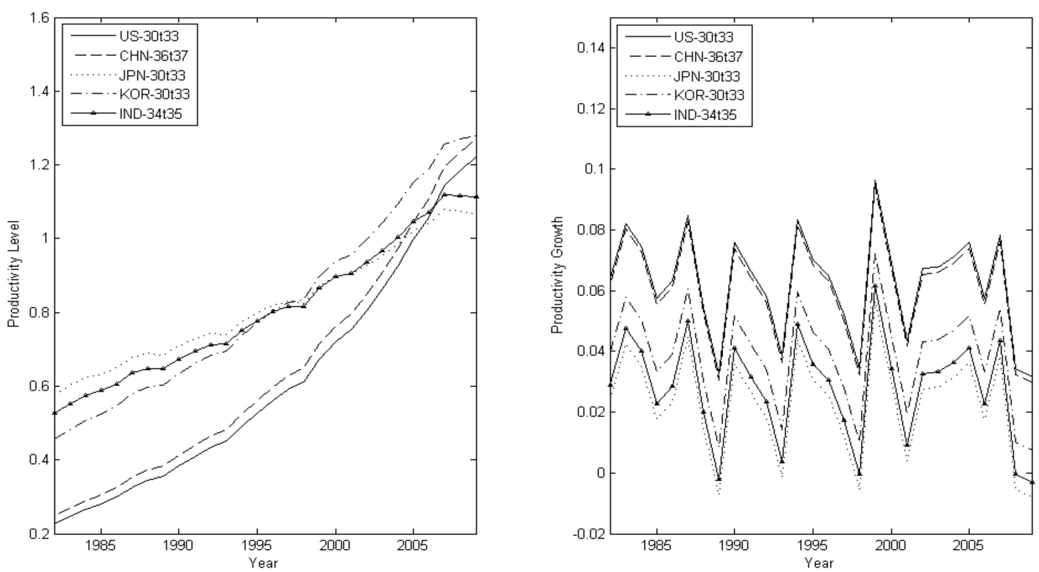


FIGURE 1

Aggregate Productivity Growth of Each Country by Model

The results for productivity levels and growth of each industry for the SDM-Up+Downstream model indicate that *Electrical and Optical Equipment* exhibits the most rapid productivity growth, not only in US but also in the industries of our sample, with an average growth rate of 6.37%. On the other hand, *Construction* is the lowest in the US and falls at the rate of -1.38%. *Electrical and Optical Equipment* is also the fastest growing industry in both Japan and Korea, with a 2.4% and 3.95% growth rate. *Manufacturing NEC and Recycling* in China and the *Transport Equipment* in India show the most rapid growth at 6.18% and 2.9%. In Figure 2 we list the industries that exhibit the highest productivity growth in the five countries based on our preferred SDM model.



(a) Productivity Level (b) Productivity Growth

FIGURE 2

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. However, when cross-sectional interactions exist, the output change of one industry due to the adjustment of the factor input is complemented by induced changes in its neighbor's inputs. We diagonalize the coefficients of independent variables and add the local interactions from their neighbor's inputs, then multiply the inverse matrix, $(I_N - \rho W)^{-1}$ in order to derive the expressions for the matrix-formed output elasticity of input factors given in Eq. (14) (LeSage and Pace, 2009). 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 the 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 4 shows the internal, external and total output elasticity of each factor input in the SDM-Up+Down model. The internal elasticities of capital per capita and intermediate inputs per capita are 0.102 and 0.589 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 capital and intermediate deepening from neighbor industries. The external elasticity of capital deepening in Table 2 is 0.051, which suggests that an industry's technological upgrading may benefit from an increase in the average organic composition of capital of the neighbor industries. The external elasticity of intermediate deepening is 0.230, which suggests that productivity of the industry may be improved when its neighbor industries are expanding the share of intermediate inputs to facilitate the vertical specialization of the production network. We can further infer that the industries in the Asia-Pacific value chain on the whole may experience a capital-augmenting and intermediate-augmenting technical progress during this period, since the marginal output of capital and intermediate are increased when the spillover effects of inputs are incorporated.

TABLE 4

Internal, External and Total Elasticity of Input Factors

SDM-Up+		Internal		External		Total	
Downstream		Elasticity	asy.t-stat	Elasticity	asy.t-stat	Elasticity	asy.t-stat
overall	*k*	0.102***	9.290	0.051***	2.813	0.153***	6.359
	m	0.589***	55.041	0.230***	5.766	0.820***	18.510
domestic	*k*	0.102***	9.290	0.047***	2.819	0.149***	6.528
	m	0.589***	55.048	0.214***	5.857	0.803***	19.601
international	*k*	0.000***	2.608	0.004***	2.712	0.004***	2.712
	m	0.000***	4.147	0.016***	4.766	0.016***	4.764

Notes: Significant at: *5, * *1 and * * * 0.1 percent.

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 4, 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 between 7% and 8% 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[14].

5.3 Hicks-neutral technical change and spatial spillovers

One advantage of our spatial model with heterogeneous 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-Up+Downstream model for all cross-sectional samples are listed as Table E.1 in Appendix E. The Domar-weighted aggregate of the five countries are shown in Figure 3. The direct and indirect effects, and their decompositions into domestic and international spillovers, are constructed from

[14] We estimate the model with spatial weight matrix constructed by the world input-output table of 2010. The international spillovers constitute about 11.3% of the external elasticity of each factor inputs. The elasticity results are given in Appendix B.

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 the SDM model, following the same process as in LeSage and Pace (2009).

The left side of Figure 3 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 a country level, China exhibits the most rapid internal technological growth measured by the direct effect at 5.05%, while the growth rates for Korea, India, Japan and US are 4.06%, 3.35%, 3.32% and 3.30%. 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 2.57%, 1.86%, 1.67%, 1.56% and 1.53%. The spillovers received account for 31% to 34% of the total technological growth of the countries in our sample.

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 4.42‰, which constitutes 23.8% of the total spillovers that Korea's industries received. China and Japan have international effects of 1.72‰ and 0.88‰ respectively, which constitutes 6.70% and 5.79% of the total spillover received by the industries of China and Japan. The international parts are relatively small for the US and India, with 3.67% and 4.77% in total received spillovers.

The right side of Figure 3 represents the technological growth of each country from the offering perspective. The direct effects are comparable to values on the left side of Figure 3. The aggregated indirect effects for Japan, China, US, India and Korea are 2.72%, 2.67%, 2.51%, 2.04% and 1.94%. However, the international spillovers that each country offers are different from those that they receive. Japan and US contribute the most international spillovers with a growth impact of 2.84‰ and 2.60‰, which accounts for 10.46% and 10.36% of their total offered spillovers. The international spillovers for China, Korea and India are 1.90‰, 1.25‰ and 0.16‰. 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. 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 2.03‰ and 1.96‰, followed by China at 0.18‰. Korea benefits most with net international spillovers at -3.17‰.

The relatively small role for India in terms of international spillovers is mirrored by its relatively small international indirect effect of 0.16‰, which is only 2% of its indirect effect, suggesting the outward international technology linkages of Indian industries are still under-developed compared to other countries in our sample.[15]

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

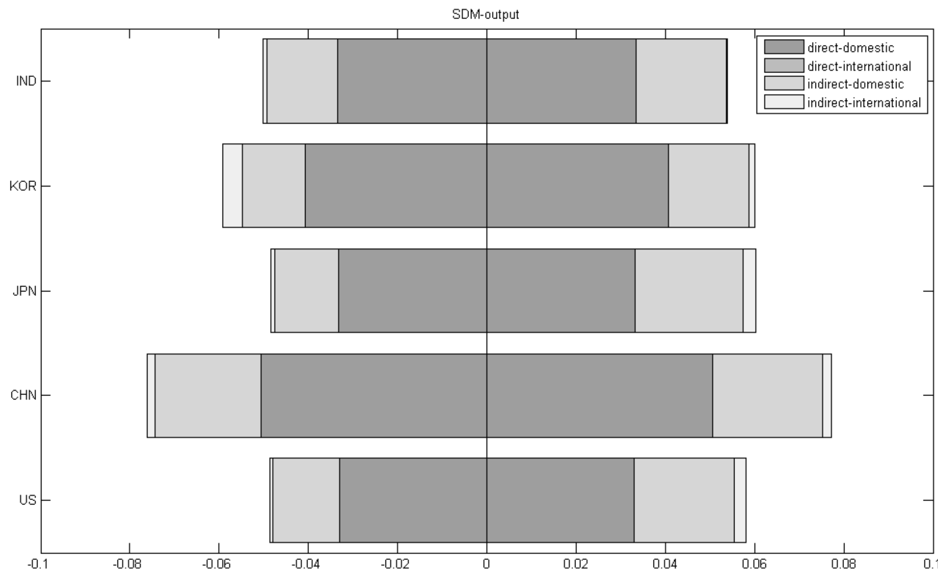


FIGURE 3

Direct and Indirect Effect of Hicks-neutral Technological Change

Figure 4 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 the industry is labeled near the dot.

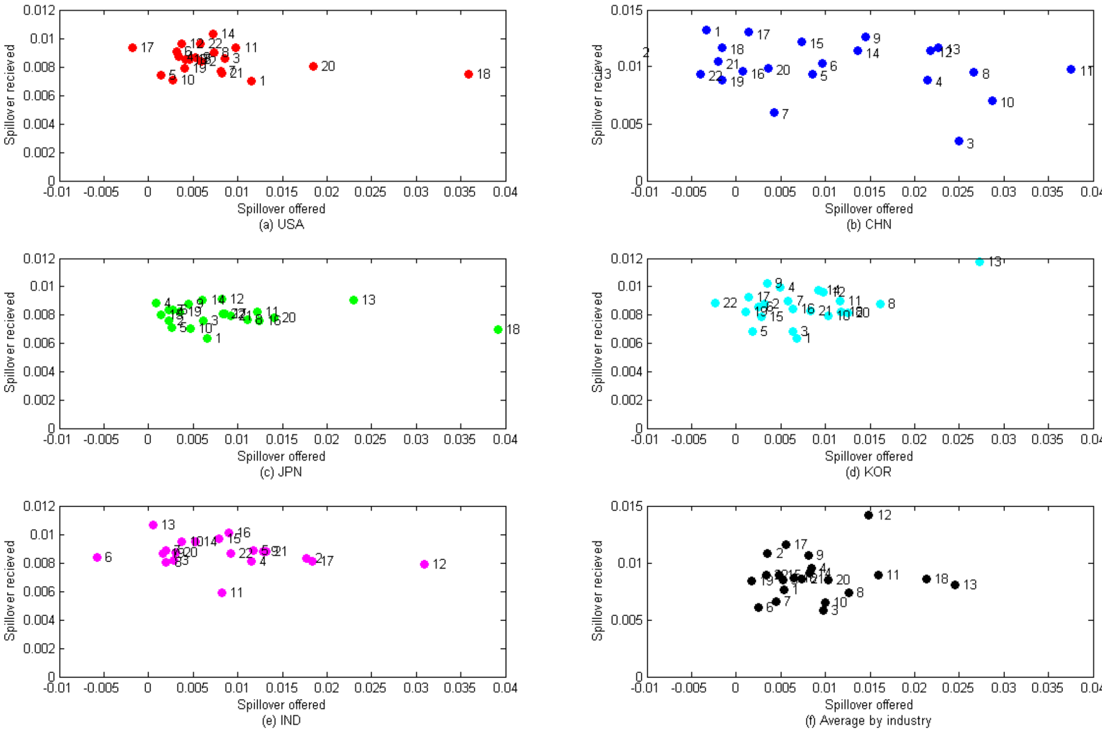


FIGURE 4

Spillover Offered and Received for All Industries

Figure 4 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 5 industries (listed in Table 1) that have the largest spillovers offered on average are Electrical and Optical Equipment (industry 13), Wholesale and Retail trade (industry 18), Basic Metals and Fabricated Metal (industry 11), Machinery, NEC (industry 12), and Chemicals and Chemical (industry 8) with indirect effects of 0.025, 0.021, 0.016, 0.015 and 0.013. The industry with the most spillover received on average is Machinery, NEC (industry 12), 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 (Table 6). 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 274,797 and 128,016 million US dollars, which contributed 68% and 32% of total output increment of the industries in our sample[16]. The industries in China benefit most from the spillovers since the increment of gross output from indirect effect is 168,170 million US dollars, which contributed 29% of total output increment.

TABLE 6

Increment of Gross Output Decomposed by Direct and Indirect Effect

(in million US dollars)

	Direct effect	Indirect effect	Total effect

[16] We remove the non-market industries from our sample. These industries in the US account 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.

US	274,797	128,016	402,813
CHN	411,240	168,170	579,410
JPN	124,590	56,657	181,247
KOR	47,667	19,810	67,478
IND	42,405	20,612	63,017

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, which contains the important ICT sector, in the five countries we study and the way in which spillovers are diffused through domestic and international supply chains for this strategic sector.

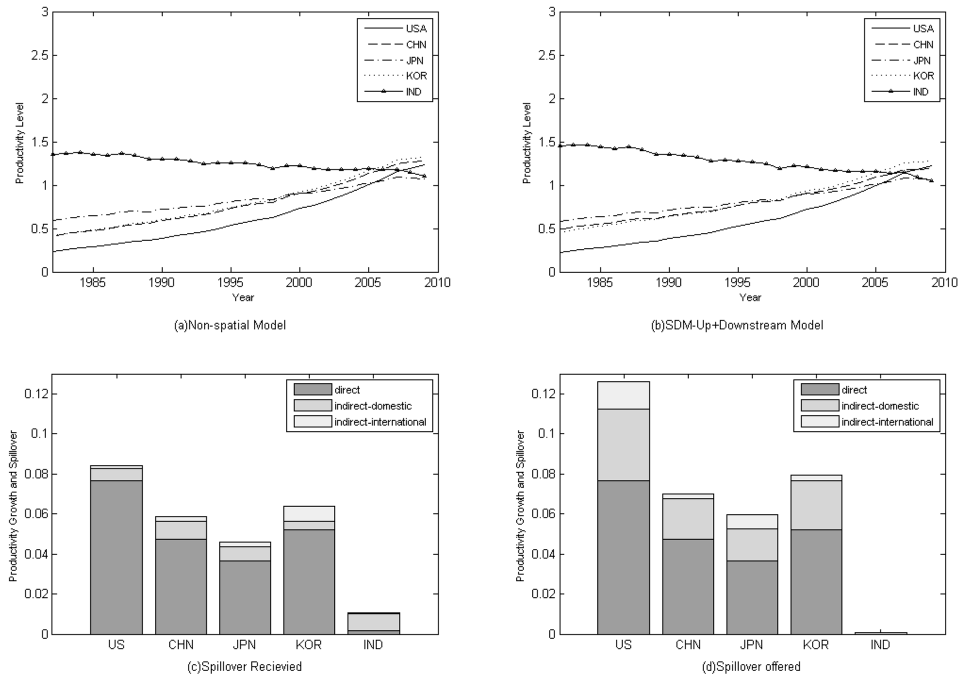


FIGURE 5

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 model and SDM-Up+Downstream 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 7.67%, is the most successful country in developing the 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 5.22%, 4.71% and 3.67%, 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 and Korea benefit most from the production network with the almost same indirect effect of 1.17%. However, the domestic indirect effect of China is 0.94%, 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 0.76%.

As shown in panel (d), the spillover of productivity growth offered by US Electrical and Optical Equipment is 4.94%, 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 2.73%, 2.29% and 2.26%. Compared with the sample average indirect effect of 0.89%, 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 1.39%, followed by Japan, Korea and China at

0.72%, 0.31% and 0.22%. Therefore, although China have the fastest growth measured by the output of the ICT sector, the US and Japan still have the largest contributions measured by the productivity growth spillover offered to other sectors and countries.

6 Conclusions

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 capital deepening, intermdediate deepening 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-Up+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 positive external elasticities for the capital and intermediate input per capita. The international indirect effect accounts for about 7.1% of the external elasticity for each factor. The Domar-weighted direct technical change growth rates for China, Korea, India, Japan and US are estimated to be 5.05%, 4.06%, 3.35%, 3.32% and 3.30%. The spillovers received account for 31% to 34% of their total technological growth and its international portion varies across the countries, with the highest, Korea, at 24% and lowest, US, at 3.67%. 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 model also provides a tool for evaluating the impact of supply chain disruption for emergent event like the outbreak of COVID-19 pandemic in appendix F. Based on the scenarios according to WTO, we simulate the impact of pandemic on the output of each country in our sample through three channels with the SDM-Up+Downstream model, i.e. reduced labor supply, intermediate shortage and the blockage of international technology spillovers.

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 the global value chain and induce a series of problems such as industry hollowing-out and unemployment. Developing countries worry that they are locked in the low value-added activities of GVCs and have 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 categories 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 endogenous time-varying social-economic spatial weight matrices may also allow us to better uncover the mechanism of technology interaction among countries and sectors within them and thus provide more insight into the sources of the dynamic spillover process.

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SUPPLEMENTAL MATERIALS AND APPENDICES FOR

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

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Industry-Specific Productivity and Spatial Spillovers through input-output linkages: Evidence from Asia-Pacific Value Chain

Abstract

Global value chains (GVCs) promote the diffusion of knowledge and technology among the participants in the production network, where the domestic and cross-border intermediate flow among the industries linked the production segments and thus accelerate the knowledge sharing and vertical specialization. This technological spillover is a main driver of technological progress and long-term growth of participating countries. This paper develops an empirical growth model that combines spatial spillovers and productivity growth heterogeneity at the industry-level. We exploit the GVCs linkages from inter-country input-output tables to describe the spatial interdependencies in technology. The spillover effects from capital deepening, intermediate deepening and Hicks-neutral technical change are identified using a spatial econometric specification. Furthermore, we use local Leontief matrices to decompose these effects into the domestic value chain spillovers transmitted within a country and the international value chain spillovers transferred across the borders. Our empirical results with the industry-level data of five Asia-Pacific countries find that ignoring the spatial interactions appears to leads to an overestimation of China's productivity growth, and underestimation of the developed countries, such as the US and Japan. The spillover effects of capital and intermediate inputs per capita are found to be significantly positive. The Domar-weighted direct technical change growth rates for China, Korea, India, Japan and US are estimated to be 5.05%, 4.06%, 3.35%, 3.32% and 3.30%. and the spillovers received account for 31% to 34% of their total technological growth. The estimated international spillover offered suggest that US is the main contributor of international knowledge diffusion, and the Electrical and Optical Equipment sector of the US has the fastest productivity growth and offers the most spillovers. These finding provide a better understanding of how technical changes are distributed and diffused within the GVCs network.

Keywords: Industry-specific productivity, Spatial panel model, Technological spillovers, Global value chain, Asia-Pacific

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

Supplemental Material-Appendices

A. Quasi-maximum likelihood estimation procedure

The Quasi-Maximum Likelihood Estimator (QMLE) is shown here for the SAR model for both the Time-Varying FE and the Time-Varying RE specification. The extension to the SDM specification is straightforward. Let $\psi = (\beta, \gamma, \rho, \sigma_v^2)'$. The log-likelihood function for Eq. (7), which we rewrite here

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

is given by:

$$\log L(\psi, \delta_i; y) = -\frac{NT}{2}\log(2\pi\sigma_v^2) + T\log|I_N - \rho W| \\ -\frac{1}{2\sigma_v^2}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(y_{it} - \rho\sum_{j=1}^{N} w_{ij} y_{jt} - X_{it}'\beta - R_t'\delta_i \right)^2, \tag{A.1}$$

where the vector X_{it} contains the regressors lnk_{it} and lnm_{it} and any other additional conditioning variables and the vector β contains the coefficients for these variables.

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

$$\frac{\partial \log L}{\partial \delta_i} = \frac{1}{\sigma_v^2}\sum_{i=1}^{N}\sum_{t=1}^{T} R_t \left(y_{it} - \rho\sum_{j=1}^{N} w_{ij} y_{jt} - X_{it}'\beta - R_t'\delta_i \right) = 0. \tag{A.2}$$

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

$$\hat{\delta}_i = (R_t R_t')^{-1} R_t \left(y_{it} - \rho\sum_{j=1}^{N} w_{ij} y_{jt} - X_{it}'\beta \right). \tag{A.3}$$

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

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

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

Time-Varying FE Estimator

Suppose that the true value of ρ is known, and is ρ^*. The within-transformed model is

$$M_Q y = \rho^* M_Q (W_N \otimes I_T) y + M_Q X\beta + \tilde{V} \tag{A.5}$$

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

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

(A.6-A.7)

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. (A.4), we can concentrate out β and σ_v^2 and write the concentrated log-likelihood function with single parameter ρ as:

$$\ln L(y;\rho)_C = \text{constant} - \frac{NT}{2}\log\left[e(\rho)'e(\rho)\right] + T\log|I_N - \rho W|, \tag{A.8}$$

By maximizing the concentrated log-likelihood function Eq. (A.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 find a numerical solution because the equation is concave in ρ . Finally, the estimators for β and σ^2 can be calculated by substituting in $\rho^* = \hat{\rho}$ into Eq. (A.6) and Eq. (A.7). Of course the time-varying fixed effects spatial model cannot identify separately all of the global and sector-specific productivity terms and growth rates and thus growth results would need to be normalized by an omitted sector.

Time-Varying Random Effects 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 $\text{cov}(\varepsilon) = \Omega$. The GLS estimator is the SAR estimator applied to the following transformed equation:

$$\begin{aligned}\sigma_v \Omega^{-1/2} y = \rho \sigma_v \Omega^{-1/2} (W_N \otimes I_T) y + \sigma_v \Omega^{-1/2} X \beta \\ + \sigma_v \Omega^{-1/2} \boldsymbol{R} \delta_0 + \sigma_v \Omega^{-1/2} \varepsilon ,\end{aligned} \tag{A.9}$$

where $\varepsilon = QU + V$, $\Omega = \text{cov}(\varepsilon) = \sigma_v^2 I_{NT} + Q(I_N \otimes \Delta) Q'$. The estimation procedure for Eq. (A.9) is comparable to the procedure for within-estimation.

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

TABLE B.1

Estimate of SDM Production Function with Spatial Weight Matrix of 2010

	(1)	(2)
	SDM-Up+Downstream	
	Time-Varying FE	Time-Varying RE
Lnk	.103***	.101***

	(.011)	(.011)
Lnm	.571***	.583***
	(.011)	(.010)
W•lnk	-.041	-.054**
	(.030)	(.027)
W•lnm	-.175***	-.122***
	(.043)	(.040)
Country-Dummy	No	Yes
Intercept		-.003
		(.045)
Time		.002
		(.002)
W•lny(ρ)	.427***	.389***
	(.027)	(.027)
σ_v^2	.009	.009
R^2	.825	.829
Adjusted R^2	.811	.814
LL	3034.411	2944.378

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

TABLE B.2

Elasticity of Input Factors by Estimation with Spatial Weight Matrix of 2010

SDM-		Internal		External		Total	
Up+Downstream		Elasticity	asy.t-stat	Elasticity	asy.t-stat	Elasticity	asy.t-stat
overall	Capital	0.103***	9.031	0.077***	3.552	0.180***	6.512
	Intermediate	0.594***	55.019	0.334***	6.940	0.928***	17.712

domestic	Capital	0.103***	9.031	-0.068***	3.579	0.171***	6.772
	Intermediate	0.593***	55.036	0.296***	7.177	0.890***	19.470
international	Capital	0.000***	3.186	-0.009**	3.323	-0.009***	3.323
	Intermediate	0.000***	4.892	0.038***	5.480	0.038***	5.479

Notes: Significant at: *5, * *1 and * * * 0.1 percent.

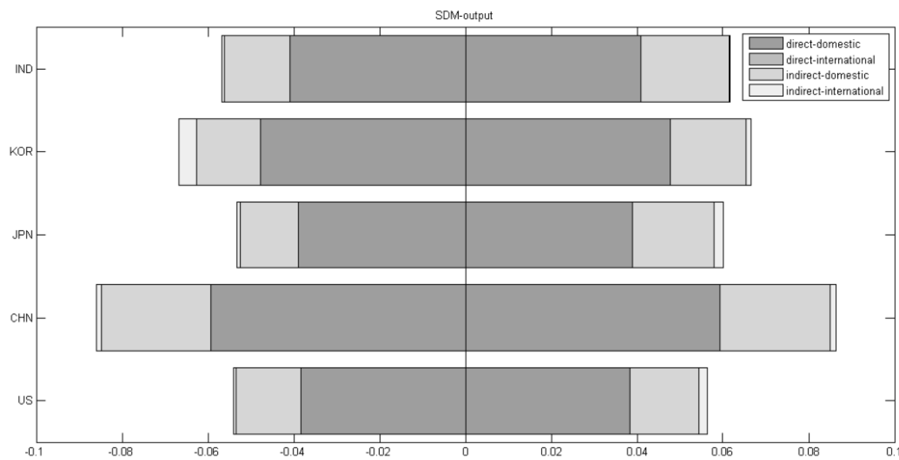


FIGURE B.1

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

C. Aggregate productivity growth of each country with different weights

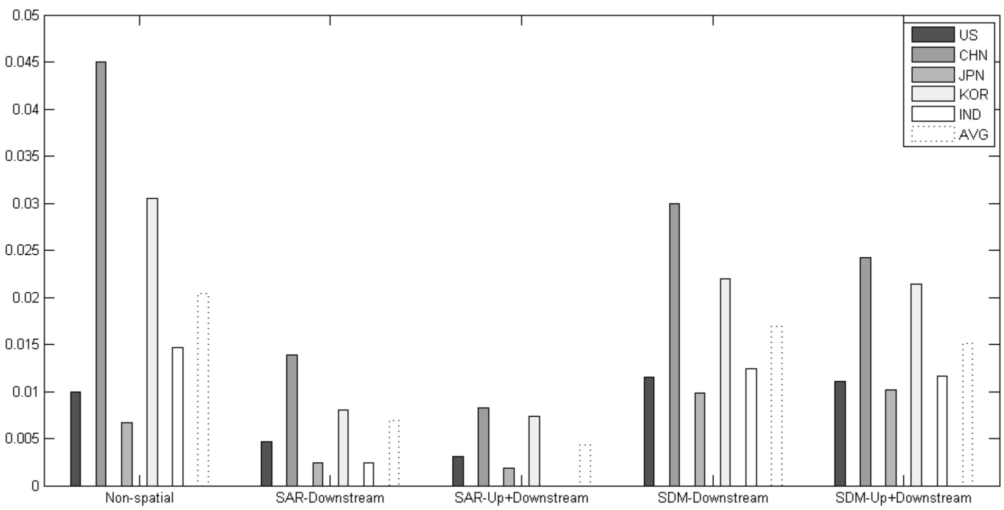


FIGURE C.1

Aggregate Productivity Growth with Domar Weights and Open-Economy Assumption

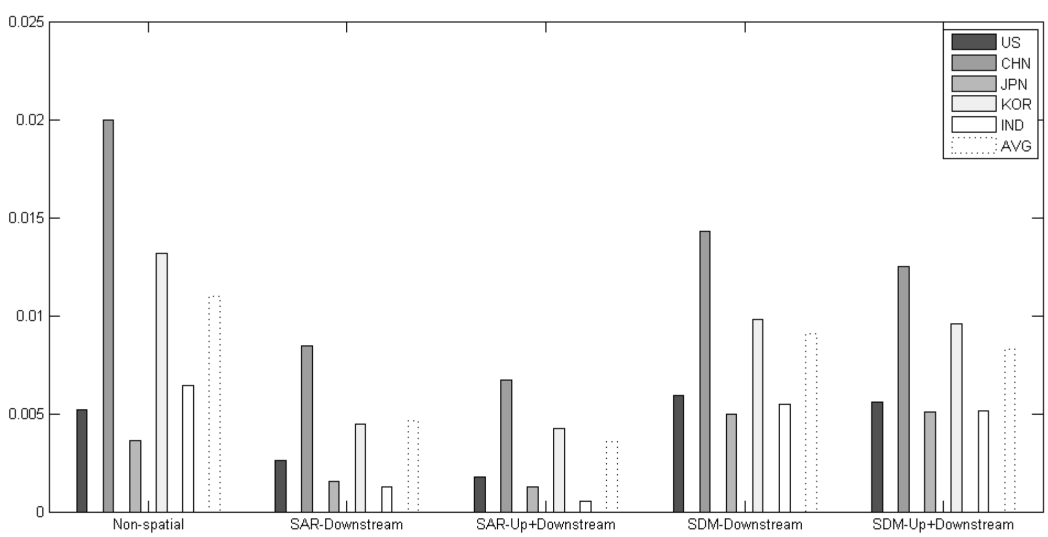


FIGURE C.2

Gross Output Weighted Average Productivity Growth of Each Country

D. Additional tests for correlated random effects and spatial autocorrelation specifications

We also have examined the possible presence of unobserved heterogeneity not addressed by the dummies for sectors, the time trends, and the country dummies using correlated random effects. We have added the means of k and m by cross section to the non-spatial and the SDM models. Their coefficients are quite small and not significant with a p-value for the F-test that they are jointly zero of about 0.50. Not surprisingly, the estimates and spillover effects remain relatively unchanged.

We also carry out a set of tests to identify the most appropriate spatial specification for the spatial weight matrix of $W2$. The first row of Table D.1 is Moran I test which suggests the autocorrelation exist, which is also consistent with the LM joint test in row 2. Row 3 suggests spatial autocorrelation in the form of an endogenous spatial lag variable assuming no SAR errors should be considered, i.e. a SAR model. Row 4 suggests spatial autocorrelation in the form of spatially autocorrelated errors assuming no spatial lag should be considered, i.e. a SEM model. The Wald test in row 5 suggests SDM model cannot be simplified to SEM model which suggests SDM model instead of SAR or SEM model is suitable in our case. The Conditional LM test (Debarsy and Ertur, 2010) in row 6 suggests no spatial correlation present when the spatial lag is already accounted for, which suggests SDM model instead of SDEM model should be used.

TABLE D.1

Tests for the Selection of Different Spatial Models

		Statistic	Probability
(1)	Moran I-no spatial autocorrelation	.1135	0
(2)	LM joint test-no spatial lag and no spatial error	502.0564	0
(3)	LM test-no spatial lag	496.8187	0
(4)	LM test-no spatial error	501.9829	0
(5)	Wald test-spatial Durbin model simplified to spatial error model	83.4370	0
(6)	Conditional LM test-no spatial error in the presence of an endogenous spatial lag	.0494	.8240

In order to further check whether any leftover spatial autocorrelation exists after we have addressed it with our SDM-time-varying random effects specification, we conduct a Moran I test on the residual of our preferred SDM model. The statistic is 0.0134 and the probability is 0.1122 which cannot reject the hypothesis of no spatial autocorrelation. We have also carried out another test on these residuals from our preferred SDM specification and re-estimated it using a nested version of the semiparametric factor model proposed by Kneip, et al. (2012) to model any possible unobserved time varying and sector-specific common factors. Again, no significantly different findings emerged from this semiparametric factor model extension of our benchmark SDM specification and the Moran tests based on the residuals after including the common factors did not reject the null hypothesis of no spatial correlations for each time period in our study.

E. Technical change and spatial spillovers for SDM-Up+Downstream model by industry

TABLE E.1

Technical Change and Spatial Spillovers for SDM-Up+Downstream Model by Industry

	Direct	Received				Offered			
		Indirect			Total	Indirect			Total
		Sum	Domestic	Int'l		Sum	Domestic	Int'l	
US.1	0.0272***	0.0070***	0.0065***	0.0005**	0.0342***	0.0115**	0.0094***	0.0021**	0.0388***
US.2	0.0184***	0.0084***	0.0082***	0.0002**	0.0268***	0.0059**	0.0056**	0.0003*	0.0243***
US.3	0.0141**	0.0086***	0.0083***	0.0002**	0.0227***	0.0086*	0.0077*	0.0009	0.0227**
US.4	0.0185***	0.0087***	0.0082***	0.0006**	0.0272***	0.0034**	0.0028**	0.0007**	0.0219***
US.5	0.0083	0.0074***	0.0070***	0.0004**	0.0158**	0.0014	0.0012	0.0002	0.0097
US.6	0.0067	0.0090***	0.0087***	0.0003**	0.0158**	0.0032	0.0027	0.0004	0.0099
US.7	0.0285***	0.0077***	0.0075***	0.0002**	0.0362***	0.0081***	0.0074***	0.0006**	0.0365***
US.8	0.0128**	0.0090***	0.0084***	0.0006***	0.0218***	0.0073*	0.0060*	0.0013*	0.0201**
US.9	0.0158***	0.0087***	0.0083***	0.0004**	0.0245***	0.0053**	0.0047**	0.0005	0.0211***
US.10	0.0181***	0.0070***	0.0067***	0.0003**	0.0252***	0.0027**	0.0024**	0.0003*	0.0209***
US.11	0.0153***	0.0094***	0.0089***	0.0005**	0.0247***	0.0098**	0.0088**	0.0011*	0.0251***
US.12	0.0104**	0.0096***	0.0089***	0.0007***	0.0200***	0.0037	0.0030*	0.0007	0.0141**
US.13	0.0768***	0.0075***	0.0060***	0.0015***	0.0843***	0.0494***	0.0354***	0.0139***	0.1262***
US.14	0.0148**	0.0103***	0.0094***	0.0009***	0.0251***	0.0072*	0.0057*	0.0015*	0.0220**
US.15	0.0273***	0.0085***	0.0081***	0.0004**	0.0358***	0.0046**	0.0040**	0.0006**	0.0319***
US.16	0.0140**	0.0085***	0.0084***	0.0001	0.0225***	0.0041*	0.0040*	0.0002	0.0181**
US.17	-0.0017	0.0093***	0.0090***	0.0003**	0.0076	-0.0018	-0.0016	-0.0002	-0.0035
US.18	0.0299***	0.0075***	0.0073***	0.0002**	0.0374***	0.0359***	0.0334***	0.0024*	0.0657***
US.19	0.0115**	0.0079***	0.0078***	0.0002*	0.0194***	0.0040*	0.0037*	0.0003	0.0154**
US.20	0.0224***	0.0080***	0.0078***	0.0003**	0.0305***	0.0185**	0.0169***	0.0016*	0.0409***
US.21	0.0167***	0.0075***	0.0074***	0.0002*	0.0243***	0.0083*	0.0077*	0.0006	0.0250***
US.22	0.0048	0.0096***	0.0094***	0.0002*	0.0144**	0.0058	0.0055	0.0004	0.0106
CN.1	-0.0035	0.0132***	0.0128***	0.0004**	0.0097	-0.0034	-0.0032	-0.0002	-0.0069
CN.2	-0.0221***	0.0115***	0.0110***	0.0005**	-0.0106	-0.0114**	-0.0109**	-0.0005*	-0.0335***
CN.3	0.0442***	0.0035*	0.0032*	0.0003*	0.0477***	0.0250***	0.0241***	0.0009*	0.0692***
CN.4	0.0389***	0.0089***	0.0075***	0.0013**	0.0478***	0.0215***	0.0165***	0.0049***	0.0604***
CN.5	0.0610***	0.0094***	0.0088***	0.0006**	0.0704***	0.0086***	0.0080***	0.0006**	0.0696***
CN.6	0.0402***	0.0103***	0.0097***	0.0005**	0.0505***	0.0096***	0.0089***	0.0007**	0.0498***
CN.7	0.0148**	0.0060**	0.0057**	0.0003*	0.0208***	0.0042*	0.0041*	0.0001	0.0190**
CN.8	0.0438***	0.0095***	0.0090***	0.0006**	0.0534***	0.0267***	0.0251***	0.0016**	0.0705***
CN.9	0.0427***	0.0127***	0.0119***	0.0008**	0.0554***	0.0145***	0.0134***	0.0011**	0.0572***
CN.10	0.0456***	0.0070***	0.0066***	0.0004**	0.0526***	0.0287***	0.0276***	0.0011**	0.0743***
CN.11	0.0394***	0.0098***	0.0091***	0.0007**	0.0492***	0.0376***	0.0357***	0.0018**	0.0769***
CN.12	0.0466***	0.0115***	0.0108***	0.0006**	0.0580***	0.0217***	0.0208***	0.0009**	0.0683***
CN.13	0.0471***	0.0117***	0.0094***	0.0024***	0.0588***	0.0226***	0.0204***	0.0022**	0.0698***
CN.14	0.0567***	0.0114***	0.0107***	0.0007**	0.0681***	0.0136***	0.0130***	0.0007**	0.0704***
CN.15	0.0739***	0.0122***	0.0116***	0.0006**	0.0861***	0.0074***	0.0068***	0.0006**	0.0812***
CN.16	0.0027	0.0096***	0.0092***	0.0004**	0.0123**	0.0008	0.0007	0.0000	0.0035
CN.17	0.0025	0.0130***	0.0126***	0.0004**	0.0155**	0.0014	0.0014	0.0000	0.0039
CN.18	-0.0017	0.0117***	0.0113***	0.0004**	0.0100	-0.0016	-0.0015	-0.0001	-0.0033
CN.19	-0.0084	0.0088***	0.0086***	0.0003*	0.0005	-0.0016	-0.0015	-0.0001	-0.0099
CN.20	0.0063	0.0099***	0.0092***	0.0006**	0.0162**	0.0036	0.0033	0.0002	0.0099
CN.21	-0.0056	0.0104***	0.0100***	0.0004**	0.0048	-0.0020	-0.0019	-0.0001	-0.0076
CN.22	-0.0184***	0.0094***	0.0083***	0.0010***	-0.0091	-0.0040**	-0.0038**	-0.0002*	-0.0225***
JP.1	0.0205***	0.0064***	0.0061***	0.0003**	0.0269***	0.0066**	0.0062**	0.0004	0.0271***
JP.2	0.0178***	0.0076***	0.0074***	0.0002*	0.0254***	0.0023**	0.0021**	0.0002*	0.0201***
JP.3	0.0112*	0.0076***	0.0073***	0.0003**	0.0187***	0.0062	0.0057	0.0004	0.0173*
JP.4	0.0048	0.0088***	0.0077***	0.0011***	0.0136**	0.0009	0.0006	0.0003	0.0056

JP.5	0.0143**	0.0071***	0.0067***	0.0004**	0.0214***	0.0026*	0.0023*	0.0003*	0.0170**
JP.6	0.0090	0.0084***	0.0081***	0.0003**	0.0174***	0.0027	0.0025	0.0003	0.0117
JP.7	0.0091*	0.0084***	0.0081***	0.0003**	0.0175***	0.0023	0.0020	0.0003	0.0114*
JP.8	0.0206***	0.0077***	0.0069***	0.0008***	0.0283***	0.0111**	0.0087**	0.0024**	0.0317***
JP.9	0.0121**	0.0087***	0.0083***	0.0005**	0.0208***	0.0045*	0.0039*	0.0005	0.0165**
JP.10	0.0192***	0.0070***	0.0067***	0.0003**	0.0262***	0.0047**	0.0040**	0.0006*	0.0239***
JP.11	0.0141**	0.0082***	0.0074***	0.0008***	0.0223***	0.0122*	0.0096*	0.0026*	0.0263**
JP.12	0.0217***	0.0092***	0.0082***	0.0009***	0.0309***	0.0083**	0.0064**	0.0018**	0.0300***
JP.13	0.0367***	0.0091***	0.0067***	0.0024***	0.0457***	0.0229***	0.0158***	0.0072***	0.0596***
JP.14	0.0169***	0.0090***	0.0080***	0.0010***	0.0259***	0.0061*	0.0048**	0.0013*	0.0229***
JP.15	0.0112**	0.0080***	0.0076***	0.0004**	0.0192***	0.0014	0.0012	0.0002	0.0126**
JP.16	0.0285***	0.0076***	0.0074***	0.0002*	0.0361***	0.0124***	0.0116***	0.0008*	0.0409***
JP.17	0.0080	0.0081***	0.0078***	0.0003**	0.0161***	0.0085	0.0078	0.0007	0.0165
JP.18	0.0254***	0.0070***	0.0067***	0.0002*	0.0323***	0.0391**	0.0367**	0.0024	0.0645***
JP.19	0.0075	0.0082***	0.0080***	0.0002*	0.0157**	0.0035	0.0033	0.0002	0.0110
JP.20	0.0183***	0.0078***	0.0076***	0.0003**	0.0261***	0.0141**	0.0128**	0.0013*	0.0324***
JP.21	0.0156***	0.0079***	0.0078***	0.0001	0.0236***	0.0092*	0.0087*	0.0005	0.0248**
JP.22	0.0117**	0.0081***	0.0079***	0.0002*	0.0197***	0.0083	0.0078	0.0005	0.0200*
KR.1	0.0169***	0.0064***	0.0055**	0.0008**	0.0232***	0.0068**	0.0066**	0.0002	0.0236**
KR.2	0.0458***	0.0088***	0.0081***	0.0006*	0.0546***	0.0032***	0.0031***	0.0000*	0.0490***
KR.3	0.0135**	0.0068***	0.0058***	0.0011**	0.0203***	0.0063*	0.0061*	0.0002	0.0198**
KR.4	0.0156**	0.0099***	0.0052***	0.0048***	0.0256***	0.0049*	0.0041*	0.0009*	0.0206**
KR.5	0.0213***	0.0069***	0.0059***	0.0010**	0.0281***	0.0019**	0.0018**	0.0000*	0.0231***
KR.6	0.0118**	0.0086***	0.0070***	0.0016**	0.0204***	0.0025*	0.0024*	0.0001	0.0144**
KR.7	0.0199***	0.0090***	0.0076***	0.0014**	0.0289***	0.0059**	0.0056**	0.0002*	0.0258***
KR.8	0.0290***	0.0088***	0.0062***	0.0026***	0.0377***	0.0161***	0.0149***	0.0013**	0.0451***
KR.9	0.0108*	0.0102***	0.0086***	0.0016**	0.0210***	0.0035	0.0033	0.0001	0.0143*
KR.10	0.0243***	0.0080***	0.0070***	0.0009*	0.0323***	0.0103***	0.0101***	0.0002*	0.0346***
KR.11	0.0171***	0.0090***	0.0068***	0.0022***	0.0261***	0.0116**	0.0110**	0.0006*	0.0288***
KR.12	0.0274***	0.0096***	0.0077***	0.0019**	0.0370***	0.0098**	0.0094**	0.0004*	0.0372***
KR.13	0.0523***	0.0117***	0.0042***	0.0076***	0.0640***	0.0273***	0.0242***	0.0031***	0.0796***
KR.14	0.0270***	0.0098***	0.0077***	0.0021**	0.0368***	0.0092**	0.0089***	0.0004**	0.0362***
KR.15	0.0156***	0.0079***	0.0067***	0.0012**	0.0235***	0.0028**	0.0027**	0.0001	0.0184***
KR.16	0.0259***	0.0085***	0.0077***	0.0008*	0.0343***	0.0063***	0.0062***	0.0001*	0.0322***
KR.17	0.0018	0.0093***	0.0081***	0.0012**	0.0110*	0.0014	0.0014	0.0000	0.0032
KR.18	0.0184***	0.0082***	0.0073***	0.0010**	0.0266***	0.0117**	0.0115**	0.0002	0.0301***
KR.19	0.0030	0.0082***	0.0074***	0.0008*	0.0112	0.0010	0.0010	0.0000	0.0040
KR.20	0.0228***	0.0082***	0.0064***	0.0018**	0.0309***	0.0125**	0.0119**	0.0006**	0.0353***
KR.21	0.0164***	0.0083***	0.0075***	0.0008*	0.0247***	0.0083**	0.0082**	0.0001	0.0248***
KR.22	-0.0040	0.0089***	0.0080***	0.0009*	0.0049	-0.0023	-0.0023	-0.0000	-0.0064
IN.2	0.0192***	0.0083***	0.0079***	0.0004**	0.0275***	0.0178**	0.0176**	0.0001*	0.0369***
IN.3	0.0100*	0.0081***	0.0078***	0.0004**	0.0181***	0.0028	0.0028	0.0000	0.0128*
IN.4	0.0229***	0.0081***	0.0079***	0.0003**	0.0311***	0.0115**	0.0114**	0.0001*	0.0344***
IN.5	0.0246***	0.0089***	0.0081***	0.0008***	0.0334***	0.0118**	0.0115**	0.0002**	0.0364***
IN.6	-0.0245***	0.0084***	0.0081***	0.0003**	-0.0161**	-0.0057**	-0.0057**	-0.0000*	-0.0302***
IN.7	0.0128**	0.0089***	0.0083***	0.0006**	0.0217***	0.0019*	0.0019*	0.0000*	0.0148**
IN.8	0.0046	0.0080***	0.0078***	0.0002*	0.0126*	0.0020	0.0020	0.0000	0.0066
IN.9	0.0250***	0.0088***	0.0081***	0.0007**	0.0338***	0.0129***	0.0127***	0.0002**	0.0379***
IN.10	0.0182***	0.0095***	0.0089***	0.0006**	0.0277***	0.0037**	0.0036**	0.0000*	0.0219***
IN.11	0.0300***	0.0059**	0.0051**	0.0007***	0.0358***	0.0082**	0.0081**	0.0001**	0.0382***
IN.12	0.0313***	0.0079***	0.0075***	0.0004**	0.0392***	0.0309***	0.0308***	0.0002*	0.0623***
IN.13	0.0017	0.0107***	0.0101***	0.0006**	0.0123*	0.0005	0.0005	0.0000	0.0022
IN.14	0.0412***	0.0095***	0.0083***	0.0012***	0.0506***	0.0052***	0.0051***	0.0001**	0.0464***
IN.15	0.0200***	0.0097***	0.0091***	0.0005**	0.0297***	0.0079**	0.0078**	0.0001*	0.0279***
IN.16	0.0312***	0.0101***	0.0094***	0.0007***	0.0414***	0.0090**	0.0088**	0.0001**	0.0402***
IN.17	0.0309***	0.0081***	0.0079***	0.0002*	0.0390***	0.0183***	0.0183***	0.0001*	0.0492***
IN.19	0.0027	0.0086***	0.0083***	0.0004**	0.0114*	0.0016	0.0016	0.0000	0.0043
IN.20	0.0273***	0.0087***	0.0086***	0.0002*	0.0360***	0.0030**	0.0030**	0.0000	0.0303***
IN.21	0.0133**	0.0088***	0.0085***	0.0002*	0.0221***	0.0132*	0.0131*	0.0001	0.0265**
IN.22	0.0232***	0.0087***	0.0085***	0.0002*	0.0319***	0.0092**	0.0092**	0.0000	0.0324***

Notes: Significant at: *5, * *1 and * * * 0.1 percent.

F. Simulation of the impact of supply chain disruption: scenarios of the COVID-19 pandemic outbreak

The outbreak of the COVID-19 pandemic is rapidly changing the world. Social distancing measures and lock-downs have changed the operation, organization, and functioning of the international economic system. The economic effects of COVID-19 have drawn more and more concern recently both from international organizations (OECD, 2020; ILO, 2020) and academia (Barro et al., 2020; McKibbin and Fernando, 2020). Since the shocks of COVID-19 to the world are unprecedented, the prediction of economic effects is a rather daunting task, made no less so by necessary assumptions about how the disease progresses. At the present there is great uncertainty about how long countries will have to keep in place or transition from social distancing measures they have undertaken and when and how international travel and transport restrictions can be relaxed and modified. Thus most of the current projection and forecast studies tend to build scenarios that make assumptions about the duration of the pandemic, the social distancing measures employed, and demand and supply responses.

Our model provides an option for estimating the compound impacts of epidemics. In our simulations, we assume the economy is affected through three different channels: (i) reduced labor supply; (ii) shortage of intermediate input supply; (iii) disruption of technology spillovers through international linkages[2].

[2] The sector demand and supply are not included in our model yet.

We follow WTO (2020) to illustrate the potential impacts of the Covid-19 pandemic on the economy based on two distinct scenarios. The first is the optimistic V-shaped and the second is the pessimistic L-shaped recovery, which we outline in Table F.1. In the V-shaped recovery the spread of the pandemic will be under control in a relatively short period because of weather conditions or medical solutions. Thus the social distancing measures can be relieved in three months. The percentage of reduced labor supply can be estimated based on Table 8, which illustrates the magnitude of influence due to the factors such as falling ill, death, and loss of productivity when working at home and the distractions that may hold, including caring for children after school closures. World merchandise trade is expected to fall by 13% on average forecasted by WTO. In the L-shaped recovery the spread of the pandemic is out of control and leads to a higher percentage of morbidity and mortality. The social distancing measures would need to last for 1 year until an effective vaccine is developed. World trade is expected to fall by 32% on average. Given the level of uncertainties, it is worth emphasizing that these scenarios should be viewed as explorations of different possible trajectories for the crisis rather than specific predictions of future developments.

TABLE F.1

Prediction of Economic Shocks Under the Two Scenarios

		V-shaped (optimistic)	L-shaped (pessimistic)
Labour supply	Morbidity	1%	4%

	Mortality		2%	2%
	Working from home		3 months	1 year
	School closures		3 months	3 months
Trade flows international intermediate supply	Exports	North America	-17.1%	-40.9%
		Asia	-13.5%	-36.2%
	Imports	North America	-14.5%	-33.8%
		Asia	-11.8%	-31.5%

Notes: The fall of international intermediate input supply is assumed to be in the same percentage with the fall of trade flows.

Source: "Trade set to plunge as COVID-19 pandemic upends global economy" WTO: 2020, https://www.wto.org/english/news_e/pres20_e/pr855_e.htm

TABLE F.2

Percent Reduction in Labor Supply and the Contribution of the Different Factors

Regions	Morbidity	Mortality	School closure	Work home	Total
V-shaped (optimistic) %					
United States	-0.12	-0.0068	-2.51	-1.25	-3.88
China	-0.12	-0.0068	-2.11	-1.25	-3.49
Japan	-0.12	-0.0068	-1.87	-1.25	-3.24
Korea	-0.12	-0.0068	-1.60	-1.25	-2.97

India	-0.12	-0.0068	-1.79	-1.25	-3.17
L-shaped (pessimistic) %					
United States	-0.48	-0.0068	-2.51	-5	-8.00
China	-0.48	-0.0068	-2.11	-5	-7.60
Japan	-0.48	-0.0068	-1.87	-5	-7.36
Korea	-0.48	-0.0068	-1.60	-5	-7.09
India	-0.48	-0.0068	-1.79	-5	-7.28

Source: "Trade set to plunge as COVID-19 pandemic upends global economy" WTO: 2020, https://www.wto.org/english/news_e/pres20_e/pr855_e.htm

The impact of the pandemic can be attributed to three aspects of our spatial production model. First, as shown in Table F.2, the annual reduction of labor supply in each country in the two scenarios is calculated based on the contribution of the four factors. Second, the fall in exports and imports will lead to a shortage of intermediate input supply. With the assumption that the domestic intermediate input is unaffected, we can estimate the magnitude of shortage of the intermediate input. Third, in our model, international trade also plays an important role as the channel of knowledge spillovers, which contributes to output growth. The fall in international trade will weaken the international intermediate linkages in the global value chain.

From the SDM model in Eq.13, we can express the logarithm of output as:

$$lnY = (I - \rho W_N \otimes I_T)^{-1}[\alpha I + (\phi - \rho\alpha) W_N \otimes I_T]k + (I - \rho W_N \otimes I_T)^{-1}[\beta I + (\varphi - \rho\beta) W_N \otimes I_T]m + (I - \rho W_N \otimes I_T)^{-1}\left(r\delta_g + QU + V\right) + lnL$$

$$= (I - \rho W_N \otimes I_T)^{-1}\left[\alpha k + \beta m + r\delta_g + QU + V + (\phi - \rho\alpha) W_N \otimes I_T k + (\varphi - \rho\beta) W_N \otimes I_T m + (I - \rho W_N \otimes I_T) lnL\right]. \quad \text{(F.1)}$$

For brevity, we assume that during this period the individual time trend and relative output elasticities of input factors are fixed, in which case Y can be expressed in terms of five components that represent the contribution of intermediate linkages UW, capital UK, labor UL, intermediate input UM and time trend UT:

$$lnY = UW(UK + UL + UM + UT), \quad \text{(F.2)}$$

where $UW = (I - \rho W_N \otimes I_T)^{-1}$, $UK = [\alpha I + (\phi - \rho\alpha) W_N \otimes I_T] lnK$, $UL = \gamma I - (\phi + \varphi) W_N \otimes I_T lnL, UM = \beta I + (\varphi - \rho\beta) W_N \otimes I_T lnM$ and $UT = r\delta_g + qU + V$.

We also assume in this baseline simulation that the capital input and Hicks-neutral technical change are not influenced by the disease, in which case the change in Y due to the shock of the pandemic can be expressed as :

$$\Delta Y = UW_1(UL_1 + UM_1 + UK + UT) - UW_0(UL_0 + UM_0 + UK + UT), \quad \text{(F.3)}$$

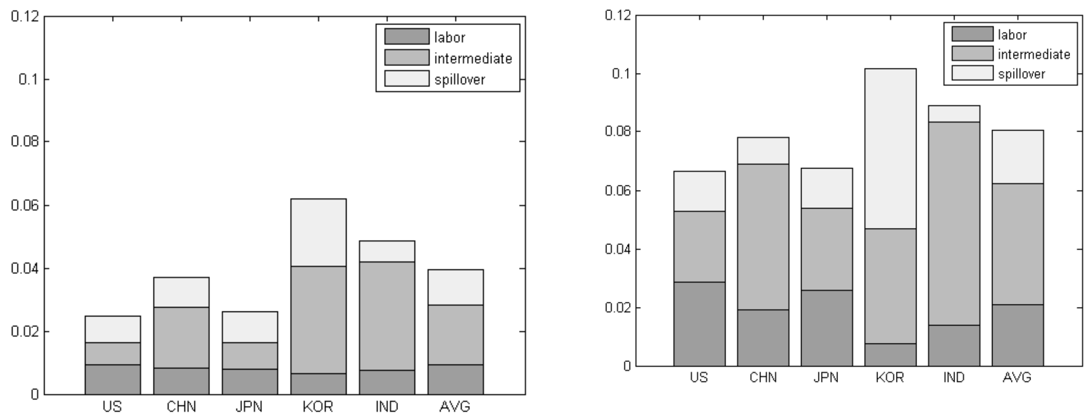
where the subscript 1 and 0 represent the state before and after the shock.

Then the contribution from each channel can be decomposed into three parts:

$$\Delta Y = \Delta UW(UL_1 + UM_1 + UK + UT) + UW_0 \Delta UL + UW_0 \Delta UM$$

$$= C(\Delta UW) + C(\Delta UL) + C(\Delta UM), \quad \text{(F.4)}$$

where $C(\Delta UW)$ represents the effect due to the reduction in technology diffusion because of the reduction in trade, $C(\Delta UL)$ represents the reduction of labor supply, and $C(\Delta UM)$ represents the effect due to a shortage of intermediate inputs. We also follow the two-polar-averaging decomposition method of Dietzenbacher and Los (1998) to calculate the average contributions of each component.



(a) Percentage of Decline in Output in Scenario 1 (b) Percentage of Decline in Output in Scenario 2

FIGURE G.1

Impact of Pandemic on the Output of Each Country through Three Channels

The estimated impacts of the pandemic on the total output of each country are shown in Figure F.1. In the V-shaped scenario, the annual average output of US, China, Japan, Korea and India industries will drop by 2.5%, 3.7%, 2.6%, 6.2%, and 4.9%. If we look at the composition of the impact by these three channels, we find that the contributions of reduced labor supply are similar in each country and leads to a 0.65%~0.95% drop in output. However, the decline due to intermediate shortage is quite different among countries. India and Korea, which have a high degree of dependence on foreign intermediate products, have an equal 3.4% output reduction due to international intermediate input supply shortages. In the US and Japan, the decline due to a shortage of intermediate inputs only leads to 0.69% and 0.84% drop, while in China it leads to 1.9% drop. Although China is the largest country in terms of the volume of merchandise trade, domestic intermediate inputs account for a relatively large proportion of intermediate input supply. From the perspective of international technology spillover, the decline in Korea of 2.2% is the largest, followed by Japan, China, US, and India at 0.96%, 0.93%, 0.83%, and 0.66%. In the L-shaped scenario, as shown in Figure 6(b), the annual decline of average output in the US, China, Japan, Korea and India is 6.64%, 7.79%, 6.75%,10.16% and 8.88%. The contributions from each of the three channels expand correspondingly.

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