Measuring Productivity Growth and Technology Spillovers through Global Value Chains: An Application to a US-Sino Decoupling[1]

Weilin Liu

Institute of Economic and Social Development

Nankai University

Tianjin, China

liuwl@nankai.edu.cn

Robin C. Sickles

Department of Economics

Rice University

Houston, Texas USA

rsickles@rice.edu

Yao Zhao

Institute of Economic and Social Development

Nankai University

Tianjin, China

zhaoyaoouc@163.com

This Draft

Aug 31, 2020

[1]We would like to thank Harry X. Wu for making available to us the China KLEMS data, Jaepil Han for providing the code for the spatial-CSS estimations.

Abstract

This paper estimates heterogeneous productivity growth and spatial spillovers through industrial linkages in the US and China from 1981 to 2010. We employ a spatial Durbin stochastic frontier model and estimates with a spatial weight matrix based on inter-country input-output linkages to describe the spatial interdependencies in technology. We estimate productivity growth and spillovers at the industry level using the World KLEMS database. The spillovers of factor inputs and productivity growth are decomposed into domestic and international effects. Most of the spillover effects are found to be significant and the spillovers of productivity growth offered and received provide detailed information reflecting interdependence of the industries in the global value chain (GVC). We use this model to evaluate the impact of a US-Sino decoupling of trade links based on simulations of four scenarios of the reductions in bilateral intermediate trade. Our estimation results and our simulations are as mentioned based on date that ends in 2010, as this is the only KLEMS data available for these countries at this level of industrial disaggregation. As the GVC linkages between the US and China have expanded since the end of our sample period our results can be viewed as informative in their own right for this period as well as possible lower bounds on the extent of the spillovers generated by an expanding GVC.

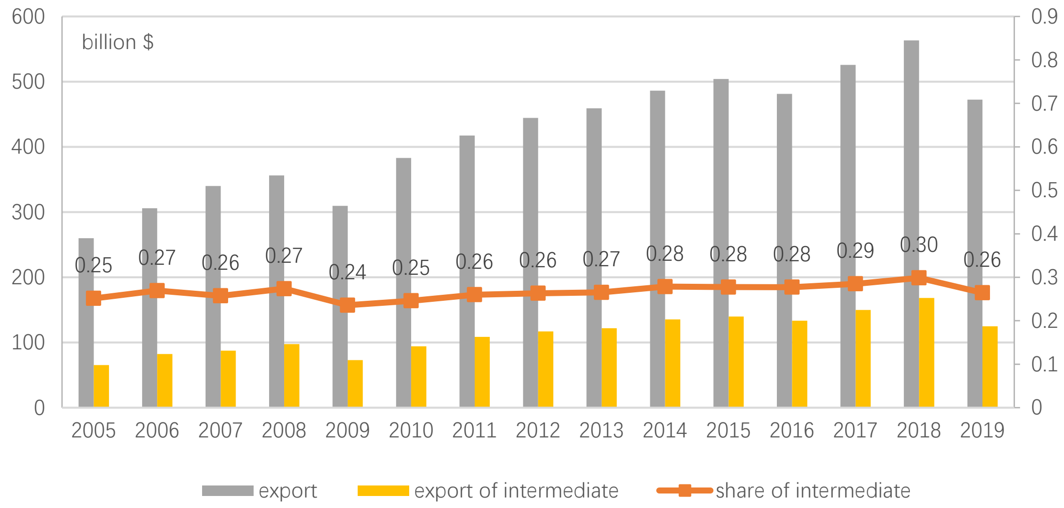
Keywords: productivity growth, technological spillovers, global value chain, US-Sino Decoupling

JEL classification codes: C23, C51, C67, D24, O47, R15, F14

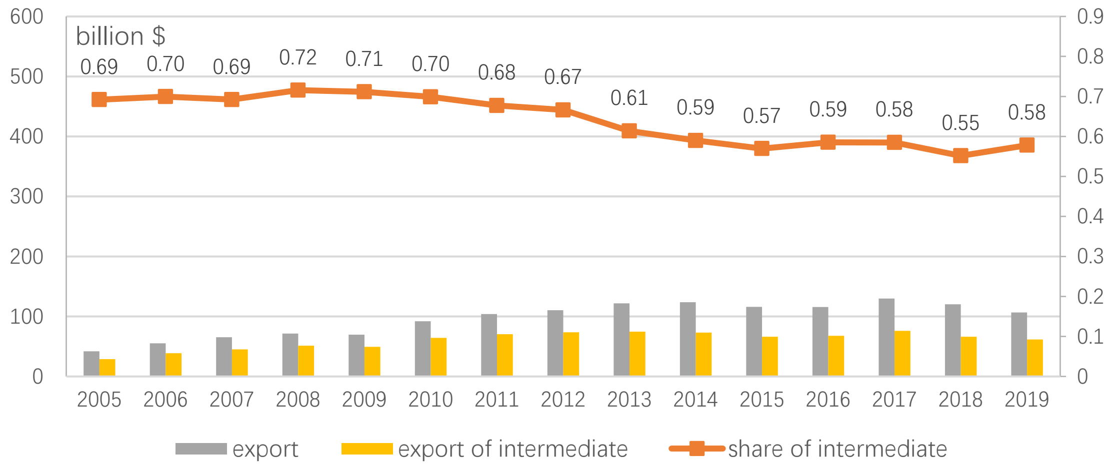
1 Introduction

The trade friction between the United States and China has been accelerating since 2018. The United States is China's largest export market and its second largest trading partner. China is the largest trading partner of the United States. The economies of both countries have a high level of interdependence. US-Sino trade is an important driving force in aggregate productivity growth and in the level of industrial development for the two countries. The occurrence and acceleration of trade frictions will have complex impacts on the economic operation of the two countries. Concurrently, such frictions will also challenge the direction and progress of globalization, which has been an important driver of world economic development in the past three decades.

The industrial division of labor in the US and China reflects the characteristics of the global value chain, which has revolutionized global economic relations (Baldwin and Lopez-Gonzalez, 2015). During the past decades, the United States typically has shown an advantage in R&D, design, logistics, and marketing, which occupy a high value-added position in the global value chain, while China has taken advantage of its large labor force and relatively low wage levels to mainly engaged in processing, assembly and other low-value-added production activities in the global value chain. The industries of the US and China are quite interdependent, with the share of intermediate product in bilateral merchandise trade between the US and China varying between 31% and 34% in 2005~2019. Intermediate inputs such as raw materials and capital components also are important mediums for knowledge dissemination, which promote growth in the scale of operation in industrial sectors as well as more intensive technologically sophisticated practices.



(a) Export of China to US



(b) Export of US to China

FIGURE 1. Share of intermediate product in the gross export between US and China

Sources: OECD Structural Analysis (STAN) databases. https://stats.oecd.org/

The role of trade in the economic growth has been widely explored in the literature and the growing evidence that technological spillovers are a major engine for economic growth since the seminal paper of Coe and Helpman (1995). A number of studies have discussed the mechanism through which technological spillovers occur due to international trade (Eaton and Kortum, 1996; Madison, 2007; Chang et al, 2011), FDI (Caves, 1996; Branstetter, 2006) and geographical proximity (Keller, 2002). Ertur and Koch (2007, 2011) developed a model based on the Solow (1956, 1957) neoclassical growth mode in a form of spatial specifications. Fingleton (2008) used spatial econometric techniques compared the standard neoclassical growth model with the model of economic geography. Nishioka and Ripoll (2012) studied the correlations between R&D embodied in intermediates and TFP. Foster-McGregor et al. (2017) found that the R&D spillovers through intermediate inputs are present and economically important. Ho et al. (2013, 2018) discussed the international spillovers of economic growth through bilateral trade with a spatial autoregressive model. Lee (2020) suggest that importing and exporting in intermediate inputs can be an important conduit of technology spillovers across borders.

Although the international spillover effects on productivity, as one of the major sources of long-term economic growth, has been recognized in many studies, the literature has often focused on national economies and in so doing has also often assumed homogeneous productivity growth among countries or sectors. The GVC network between US and China is built on the basis of specialized labor division. The operation and coordination of the GVCs take place through upstream-downstream sectoral linkages. Therefore, an analysis of the pattern of interaction between US and China requires an investigation into industry level linkages. Moreover, heterogeneity among sectors should be considered because of the diversified technical and economic features in each industrial sector as well as changes in the structure of the industrial sectors in both countries during the decades since China entered the WTO. Durlauf (2000, 2001) and Brock and Durlauf (2001) discussed the possible bias of homogenous assumption in modeling economic growth across countries. Jorgenson et al. (2012) suggest that some key industries such as IT-producing and IT-using industries play a predominant role as drivers of productivity growth. The list of the products that are no longer subject to additional tariffs in US-Sino bilateral are concentrated in several specific industries instead of the full set of product categories. A sector-level analysis of productivity growth and spillovers thus permits a more detailed evaluation of trade friction impacts leading to better informed decision-makers of both tactical and strategic trade policy measures.

Our paper provides a novel model to measure industry-specific productivity growth and spillovers in GVC, and with this model we evaluate the impact of trade frictions between the US and China based on a set of scenarios that vary in the intensity of trade conflicts. We propose a spatial production function that allows productivity growth to vary by sectors. We use the neoclassical growth model (Solow, 1956, 1957) with the inclusion of knowledge spatial externalities in the form of Ertur and Koch (2007). The intermediate flows from the World Input-Output tables are used to construct the spatial weights matrix to represent the economic distance between the industries in China and the US. The heterogeneous technical progress of cross-sections in the Solow residue is identified based on the estimation technique developed by Cornwell et al. (1990) by allowing for an industry-specific function of time. In our empirical analysis, we follow Glass et al. (2015) and calculate the direct, indirect and total marginal effects of inputs and time trends on gross output, so that we can explore the magnitude and distribution of knowledge diffusion among the industries within the GVC network. We also consider the direction of knowledge diffusion by distinguishing between sectors in the US and in China that receive and offer knowledge externalities in order to identify which sectors of both countries are playing a leading role in contributing the most in the GVC network and which industries are benefiting most from the spillovers. Furthermore, we propose a decomposition method to identify the spillovers transmitted within the border of one country and the spillovers across the borders, so that we can further investigate the distinction between the spillovers through domestic and international linkages.

This paper is organized as follows. In section 2 we outline the spatial production model with heterogeneity in technical progress using spatial Durbin model (SDM) specifications, and then use our approach to measure the spatial spillovers of the inputs and of Hicks-neutral technical change. We also provide the methodology to decompose domestic and international spillovers using the local Leontief matrices. Section 3 discusses our estimation strategy. Section 4 presents the industry-level data of the US and China, as well as the World Input-Output tables we use to construct the spatial weight matrix. In section 5 we estimate the production function using our methodology and discuss the productivity spillovers through the GVCs between US and China. Section 6 provides several sets of simulations of the impact of US-Sino decoupling based on differing scenarios of deteriorating trade links between the US and China. Section 7 concludes.

Our estimation results and our simulations are as mentioned based on date that ends in 2010, as this is the only KLEMS data available for these countries at this level of industrial disaggregation. As the GVC linkages between the US and China have expanded since the end of our sample period our results can be viewed as informative in their own right for this period as well as possible lower bounds on the extent of the spillovers generated by an expanding GVC.

2 Model

2.1 Heterogeneous Technical Progress in Solow Residual

Consider the aggregate Cobb-Douglas panel production function with three factor inputs capital, labor, and intermediates:

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

In keeping with the literature and on recent studies using the KLEMS data (Sanidas and Park, 2011; Oulton, 2012; Wu, 2016), we consider a nonspatial constant returns to scale technology wherein $\alpha + \beta + \gamma = 1$. Y_{it} is the total output and K_{it}, M_{it}, and L_{it} are the capital, labor, and intermediate input levels. A_{it} is the aggregate level of productivity, which differs among industries and time periods and is given by:

$$A_{it} = e^{\delta_i t + v_{it}}, \tag{2}$$

where Ω_i is the individual initial technology state and δ_i are the coefficients that depend on *i*. We relax the assumption of Solow model (Solow, 1956; Swan, 1956; Ertur and Koch, 2007) about the identical technical progress in cross-sections by allowing for an industry-specific time trend.

The non-spatial production function per unit of labor is thus:

$$y_{it} = e^{\Omega_i + \delta_i t + v_{it}} k_{it}{}^{\alpha} m_{it}{}^{\beta}, \tag{3}$$

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

The level of time-varying productivity for industry/sector i, $\delta_i t$, can be decomposed into a global time trend $\delta_g t$ and an industry-specific term $u_i t$. If we add the usual idiosyncratic error v_{it}, assumed to be *iid* $N(0, \sigma_v^2)$ to the average production function in (3) then it can be rewritten in logarithm form as the linear regression model

$$\ln y_{it} = \alpha \ln k_{it} + \beta \ln m_{it} + \Omega_i + \delta_g t + u_i t + v_{it} \,. \tag{4}$$

Cornwell et al. (1990) considered a model such as (4), where the vector u_i is assumed to be *iid* with zero mean and covariance matrix Δ. They further decomposed the time-varying progress of technology for each industry by allowing for the effects $\alpha_{it} = \omega_i + u_i t$ to contain a time varying inefficiency term that could be identified after the average production function (3) was estimated by standard linear panel methods using time-varying fixed effects, random effects, and correlated random effects. We do not pursue this further decomposition of productivity change into an innovation and efficiency component based on the stochastic frontier model and condition our model interpretations on the standard neoclassical average production literature[2]. We can see that if heterogeneous productivity growth is not time-varying and thus u_i is zero, then the model will be consistent with the basic Solow model and we can estimate Eq. (4) with standard panel data methods.

2.2 Spatial Interdependence and Technology Spillovers

In order to allow for structural cross-sectional linkages among sectors across the two countries in our study, the US and China, we extend Eq. (4) to a spatial form production function following Ertur and Koch (2007). They model technology A_{it} as a function of a common global time trend, per worker capital, and a spatial lag of a country's neighbor's technology. We extend Eq. (4) by allowing for the interdependence among industries/sectors that comes from knowledge diffusion via input-output linkages. The

[2]For a further discussion of these differences see chapter 6 and 9 of Sickles and Zelenuyk (2019).

strength of the linkage from industry i to its neighbor industry j is expressed as w_{ij}. We assume that the technical spillovers are influenced by the neighbor's technology, input levels of per-worker physical capital k_{jt}, and per-worker intermediate input m_{jt}. The impact takes effect through the spatial linkages. Technology is then written as:

$$A_{it} = e^{\Omega_i + \delta_i t + v_{it}} \prod_{j \neq i}^{N} A_{jt}^{\rho w_{ij}} \prod_{j \neq i}^{N} k_{jt}^{\phi w_{ij}} \prod_{j \neq i}^{N} m_{jt}^{\varphi w_{ij}} . \tag{5}$$

Taking logarithms of Eq. (5), A_{it} can be rewritten as:

$$\ln A_{it} = \Omega_i + \delta_i t + v_{it} + \rho \sum_{j \neq i}^{N} w_{ij} \ln A_{jt} + \phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt}$$

$$= \left(1 - \rho \sum_{j=1}^{N} w_{ij} \right)^{-1} (\Omega_i + \delta_i t + v_{it} + \phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt}) . \tag{6}$$

The production function per worker can then be written in a Spatial Durbin form[3] as:

$$\ln y_{it} = \left(I - \rho \sum_{j \neq i}^{N} w_{ij} \right)^{-1} (\Omega_i + \delta_i t + v_{it} + \phi \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j \neq i}^{N} w_{ij} \ln m_{jt}) + \alpha \ln k_{it} + \beta \ln m_{it} ,$$

or

$$\ln y_{it} = \rho \sum_{j \neq i}^{N} w_{ij} \ln y_{jt} + \alpha \ln k_{it} + \beta \ln m_{it} + (\phi - \alpha\rho) \sum_{j \neq i}^{N} w_{ij} \ln k_{jt} + \left(\varphi - \beta\rho \right) \sum_{j \neq i}^{N} w_{ij} \ln m_{jt} + \Omega_i + \delta_i t + v_{it} . \tag{7}$$

We can rewrite this in matrix form as:

$$y = \rho \left(W_N \otimes I_T \right) y + k\alpha + m\beta + \Omega + r\delta_g + qU + V$$

$$+ (\phi - \alpha\rho) \left(W_N \otimes I_T \right) k + \left(\varphi - \beta\rho \right) \left(W_N \otimes I_T \right) m , \tag{8}$$

where y, k, m and V are $NT \times 1$ vectors, Ω is $\Omega_i \otimes \iota_T$, ι_T is a T dimensional vector of ones, $r = \iota_N \otimes R$, ι_N is N dimensional vector of ones, $R=1,\ldots,T$, $q = diag\left(\iota_N \right) \otimes R$, is $NT \times N$ matrix, and U is an $N \times 1$ vector.

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

2.3 Spillovers of Technology through Factor Input and Technical change

The production technology in our model is characterized by the spatial externalities across industries (Glass, et al., 2015). The elasticities of capital and intermediate input per worker in the spatial model are not only determined by α and β, but also by the external elasticities of capital and intermediate inputs per worker from neighbors' industries. Thus, total effects are a combination of direct and indirect effects that incorporate the spillover effects. As an example, the total effect of a change in per-worker capital is gotten by differentiating Eq. (7) with respect to per-worker capital and the matrix of direct and indirect effects for each industry are written as:

$$\Xi_k \equiv \left[\frac{\partial \ln y}{\partial \ln k_1}, \frac{\partial \ln y}{\partial \ln k_2}, \cdots, \frac{\partial \ln y}{\partial \ln k_N}\right]_t = \begin{bmatrix} \frac{\partial \ln y_1}{\partial \ln k_1} & \frac{\partial \ln y_1}{\partial \ln k_2} & \cdots & \frac{\partial \ln y_1}{\partial \ln k_N} \\ \frac{\partial \ln y_2}{\partial \ln k_1} & \frac{\partial \ln y_2}{\partial \ln k_2} & \cdots & \frac{\partial \ln y_2}{\partial \ln k_N} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial \ln y_1}{\partial \ln k_1} & \frac{\partial \ln y_1}{\partial \ln k_1} & \cdots & \frac{\partial \ln y_1}{\partial \ln k_1} \end{bmatrix}_t \tag{9a}$$

$$= \left(I - \rho W_N\right)^{-1} \begin{bmatrix} \alpha & w_{12}\left(\phi - \alpha\rho\right) & \cdots & w_{1N}\left(\phi - \alpha\rho\right) \\ w_{21}\left(\phi - \alpha\rho\right) & \alpha & \cdots & w_{2N}\left(\phi - \alpha\rho\right) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\left(\phi - \alpha\rho\right) & w_{N2}\left(\phi - \alpha\rho\right) & \cdots & \alpha \end{bmatrix}. \tag{9b}$$

The direct effect of per-worker capital can then be calculated by taking the mean of the diagonal elements of the matrix in Eq. (9b) and we denote the average marginal effect as $\xi_k^{\ D}$ for all the industries. The indirect effect of per-worker capital, $\xi_k^{\ I}$, is calculated by taking the average of row sums of the non-diagonal elements of the matrix in Eq. (9b). The total effect, which is comparable to the overall input elasticity of capital per unit labor, is $\xi_k^{\ T} = \xi_k^{\ D} + \xi_k^{\ I}$. The direct, indirect and total effect of per-worker intermediate input, denoted as $\xi_m^{\ D}$, $\xi_m^{\ I}$ and $\xi_m^{\ T}$, are calculated in the same way. Since the production function is subject to constant to scale, the direct effect of labor is $\xi_l^{\ D} = 1 - \xi_k^{\ D} - \xi_m^{\ D}$ and the indirect effect of labor is $\xi_l^{\ I} = -\xi_k^{\ I} - \xi_m^{\ I}$. The total effect of labor $\xi_l^T = 1 - \xi_k^T - \xi_m^T$, which suggests the assumption of constant returns to scale still holds in the spatial settings.

The difference between the direct effect in spatial model and the elasticity in non-spatial model is that the direct effect also considers the feedback process that originates from the input change of an industry which then influences the neighbor industries' output, then rebounds back and induces the change in the output of the industry itself. The indirect effect is the external elasticity expressed as a spatial multiplier due to the interdependence among the industries. It refers to the output percentage change of an industry caused by a 1% increase in the sum of inputs across all the neighbor industries. The total elasticity is the summation of direct and indirect effects and is the percentage change of an industry due to a 1% increase in the sum of inputs across all the industries in the sample.

The Hicks-neutral technical change also generates spatial spillovers among the industries. However, because technical change is industry-specific, the spillover that an industry received or offered will be not only dependent on the strength of the linkages with its neighbor, but also dependent on the technical change of the neighbors. These spillovers are expressed as:

$$\Lambda_t \equiv \left[\frac{\partial \ln y}{\partial \ln t}\right]_t = \left(I - \rho W_N\right)^{-1} \begin{bmatrix} \delta_1 & 0 & \cdots & 0 \\ 0 & \delta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_n \end{bmatrix}_t = \begin{bmatrix} \tilde{w}_{11}\delta_1 & \tilde{w}_{12}\delta_2 & \cdots & \tilde{w}_{1n}\delta_n \\ \tilde{w}_{21}\delta_1 & \tilde{w}_{22}\delta_2 & \cdots & \tilde{w}_{2n}\delta_n \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}_{n1}\delta_1 & \tilde{w}_{n2}\delta_2 & \cdots & \tilde{w}_{nn}\delta_n \end{bmatrix}, \quad (10)$$

where $\tilde{w}_{ij}$ is the *ij*th element of $\left(I - \rho W_N\right)^{-1}$. The direct effect of sector-specific innovation, proxied by the time trend of industry i and denoted as g_i^D, is the ith diagonal element of the matrix in Eq. (10) and indicates the average productivity change of industry i itself. The indirect effect of the sector-specific time trend reflects the exchange of knowledge among industries and is represented by the off-diagonal elements in Eq. (10). The row summation of the off-diagonal elements g_i^{Ir} can be interpreted as the aggregate spillover that industry i received from other industries and the summation by column of the off-diagonal elements g_i^{Io} is the aggregate spillover that industry i offers to other industries. We can express the total effect g_i^{Tr} by $g_i^{Tr} = g_i^{D} + g_i^{Ir}$, which can be interpreted as the compound productivity change of industry i from the perspective of receiving. Correspondingly, the total effect $g_i^{To} = g_i^{D} + g_i^{Io}$ represents compound productivity change that industry/sector i provides for the whole economic system composed of US and Chinese industries.

2.4 Spillovers within Country and across Border

The spillover of industries along GVCs not only happens among the sectors within a country, but also transmits across the border through the international input-output linkages. The first multiplier in Eq.(9b), $G_N \equiv \left(I_N - \rho W_N\right)^{-1}$, represents the global interaction of all the industries from both countries. Then G_N can be expressed in the form of block matrix as follows

$$G_N = \begin{bmatrix} G_{UU} & G_{UC} \\ G_{CU} & G_{CC} \end{bmatrix}, \tag{11}$$

where G_{UC} is the block matrix of the global multiplier that refers to the global spillover between the industries groups of the US and China. G_{UU} is the block matrix of the global multiplier that represents the global spillover among the group of industries of the US. However, the global multiplier G_{UU} also includes the international spillovers that originates from the industries of the US, then transmits to the industries of China and finally rebounds back to the industries of the US. To solve this problem, we split the spatial weight matrix that based on the inter-country input-output table of the economy system of the US and China into a four block matrices as following:

$$W_N \equiv \begin{bmatrix} W_{UU} & W_{UC} \\ W_{CU} & W_{CC} \end{bmatrix}, \tag{12}$$

where W_{UU} is $F_U \times F_U$ matrix, W_{UC} is $F_U \times F_C$ matrix, W_{CU} is $F_C \times F_U$ matrix, W_{CC} is $F_C \times F_C$ matrix, F_U and F_C are the number of sectors in the US and China. W_{UU} and W_{CC} represent the linkages of the industries within the US and China. W_{UC} and W_{CU} represent the linkage of the industries between the US and China. Then in the same way of constructing the global multiplier G_N, we can define the local multiplier of the US and China as $H_{UU} \equiv \left(I_F - \rho W_{UU}\right)^{-1}$ and $H_{CC} \equiv \left(I_F - \rho W_{CC}\right)^{-1}$, which represents the local industrial interaction within the border of US and China.

From the definition of G_N, we have:

$$G_N\left(I_N - \rho W_N\right) = \begin{bmatrix} G_{UU} & G_{UC} \\ G_{CU} & G_{CC} \end{bmatrix} \begin{bmatrix} I_F - \rho W_{UU} & -\rho W_{UC} \\ -\rho W_{CU} & I_F - \rho W_{CC} \end{bmatrix} = \begin{bmatrix} I_N & 0 \\ 0 & I_N \end{bmatrix}, \quad (13)$$

And can then express G_{UU} as the summation of the following two terms

$$G_{UU} = \left(I_N + \rho G_{UC} W_{CU}\right)\left(I_F - \rho W_{UU}\right)^{-1} = H_{UU} + \rho G_{UC} W_{CU} H_{UU}, \quad (14)$$

where H_{UU} is the pure domestic multiplier and $\rho G_{UC} W_{CU} H_{UU}$ reflects the contribution due to the diffusion of technology that is first exported from the US to China, is then reimported back to the US, and finally is diffused within the industries of the US.

In the same way, we can derive G_{CC} as:

$$G_{CC} = \left(I_N + \rho G_{CU} W_{UC}\right)\left(I_F - \rho W_{CC}\right)^{-1} = H_{CC} + \rho G_{CU} W_{UC} H_{CC}, \quad (15)$$

and the global multiplier, G_N then can be expressed by the summation of two components:

$$G_N = \begin{bmatrix} G_{UU} & G_{UC} \\ G_{CU} & G_{CC} \end{bmatrix} = \begin{bmatrix} H_{UU} & 0 \\ 0 & H_{CC} \end{bmatrix} + \begin{bmatrix} \rho G_{UC} W_{CU} H_{UU} & G_{UC} \\ G_{CU} & \rho G_{CU} W_{UC} H_{CC} \end{bmatrix}. \quad (16)$$

The first component in the right most expression of Eq. (16) is a block diagonal matrix that captures the effect of the domestic interaction among the industries within the US and China and the second component captures the international interaction between the

US and China, which is defined as the international multiplier. The diagonal blocks in the international multiplier matrix represent the feedback effects, and the off-diagonal blocks represent the diffusion between the groups of industries of the US and China.

In the expression of the elasticity of inputs in Eq.(9b), the second multiplier can also be decomposed into domestic linkages and international linkages by splitting the matrix into four blocks as follows:

$$\widehat{W}_k \equiv \begin{bmatrix} \alpha & w_{12}(\phi-\alpha\rho) & \cdots & w_{1N}(\phi-\alpha\rho) \\ w_{21}(\phi-\alpha\rho) & \alpha & \cdots & w_{2N}(\phi-\alpha\rho) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi-\alpha\rho) & w_{N2}(\phi-\alpha\rho) & \cdots & \alpha \end{bmatrix} = \begin{bmatrix} \widehat{W}_{k-UU} & \widehat{W}k_{k-UC} \\ \widehat{W}_{k-CU} & \widehat{W}k_{k-CC} \end{bmatrix}. \quad (17)$$

The direct and indirect effects of per worker capital can be decomposed into a domestic effect Ξ_{k-dom} and an international effect Ξ_{k-int}:

$$\Xi_{k-dom} = \begin{bmatrix} H_{UU} & 0 \\ 0 & H_{CC} \end{bmatrix} \begin{bmatrix} \widehat{W}_{k-UU} & 0 \\ 0 & \widehat{W}_{k-CC} \end{bmatrix}, \quad (18)$$

$$\Xi_{k-int} = \begin{bmatrix} H_{UU} & 0 \\ 0 & H_{CC} \end{bmatrix} \begin{bmatrix} 0 & \widehat{W}_{k-UC} \\ \widehat{W}_{k-CU} & 0 \end{bmatrix} + \begin{bmatrix} \rho G_{UC} W_{CU} H_{UU} & G_{UC} \\ G_{CU} & \rho G_{CU} W_{UC} H_{CC} \end{bmatrix} \begin{bmatrix} \widehat{W}_{k-UU} & \widehat{W}_{k-UC} \\ \widehat{W}_{k-CU} & \widehat{W}_{k-CC} \end{bmatrix}, \quad (19)$$

where Ξ_{k-dom} is the product of the two block diagonal matrices that represent the interaction within the border of each country and Ξ_{k-int} is the remaining portion of $\Xi_k - \Xi_{k-int}$ that includes all the interactions that cross the border of each country. Then, in the same way we can calculate the direct, indirect and total effect of per-worker capital, the domestic counterparts can be derived and are denoted as ξ^D_{k-dom} , ξ^I_{k-dom} and ξ^T_{k-dom}, while the international counterparts are denoted as ξ^D_{k-int} , ξ^I_{k-int} and ξ^T_{k-int}.

The spillovers that come from domestic economic activity and the spillovers that come from international economic activity can be separately identified based on our method. The spillover of technical change Λ_t can be decomposed into domestic spillover Λ_{t-dom} and international spillover Λ_{t-int} in Eq. (20) and Eq. (21). Then we can express the corresponding direct, indirect and total counterparts as:

$$\Lambda_{t-dom} = \begin{bmatrix} H_{UU} & 0 \\ 0 & H_{CC} \end{bmatrix} \begin{bmatrix} \delta_1 & 0 & \cdots & 0 \\ 0 & \delta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \delta_n \end{bmatrix} \tag{20}$$

$$\Lambda_{t-int} = \begin{bmatrix} \rho G_{UC} W_{CU} H_{UU} & G_{UC} \\ G_{CU} & \rho G_{CU} W_{UC} H_{CC} \end{bmatrix} \begin{bmatrix} \delta_1 & 0 & \cdots 0 \\ 0 & \delta_2 & \cdots 0 \\ \vdots & \vdots & \ddots \vdots \\ 0 & 0 & \cdots \delta_n \end{bmatrix}. \tag{21}$$

3 Estimation

The production function given in Eq. (8) can be estimated as a typical spatial-Durbin model based on a neoclassical average production technology with the implied assumption that every unit of production is efficient in converting the various inputs into final aggregate. One can also allow for this assumption to be relaxed and thus allow each industry in the global value chain to potentially exhibit inefficiency, in which case Solow-type residual productivity growth of each industry is decomposed into an efficiency and technical progress component. Instead of using the standard SDM model, one can combine the spatial model with a stochastic frontier analysis (SFA) approach to estimate the production function with time-varying productivity, composed of the usual productivity time trend that captures overall technical innovation that is appropriable by all sectors and countries and an efficiency component that is sector-specific. In order to avoid strong distributional assumptions for the residual of the panel production frontier, Schmidt and Sickles (SS) (1984) and Cornwell, Schmidt, and Sickles (CSS) (1990) assume inefficiency to be unit-specific and relative inefficiency to be derived from a simple transformation of the residuals after the average production function is estimated. We relax the time-invariant assumption of SS by allowing for time-varying productivity via the CSS model specification. However, instead of focusing on the decomposition of productivity into an innovation and an efficiency component after estimation, we focus on total productivity growth.

Following the approach of the CSS model, we can estimate Eq. (4) via a within transformation, generalized least squares, and an efficient instrumental variable approach. To estimate the spatial model of Eq. (8), however, which has the additional spatially correlated variables, we use a quasi-maximum likelihood estimation (QMLE) method. By using QMLE, we are able to minimize the number of parameters to be estimated with concentrated likelihood function instead of using the full likelihood function. The closed-form solutions for a set of parameters are substituted into the likelihood function and then the spatial coefficient is the only parameter left in the concentrated likelihood function. The maximized full likelihood by optimizing the concentrated likelihood is known to give the same maximum likelihood estimates (LeSage and Pace, 2009). The details of estimation are developed in Han (2016).

For the parameters except for the spatial autoregressive parameter ρ, closed-form solutions can be obtained by the first-order conditions of the likelihood functions of Eq. (8). The spatially weighted independent variables are treated as additional regressors. By substituting of the closed-form solutions into the likelihood functions, we can formulate the concentrated likelihood functions with ρ as the only unknown variable. Then by maximizing the concentrated likelihood function, $\hat{\rho}$ can be obtained. Hence all other parameters can be found using $\hat{\rho}$.

4 Data

International comparisons concerning patterns of output, input and productivity are very challenging (Jorgenson, et al., 2012) for the involvement of combining and matching of various datasets. The data for the US is collected from the WORLD KLEMS database, which provides the quantity and price indices of gross output and inputs including capital service, labor service and intermediate by industry. The reference year is 2005. The data for China comes from the China Industrial Productivity (CIP) Database. The latest version is CIP 3.0 released in 2015. The database provides the real and nominal gross output and intermediate input (Wu and Keiko, 2015; Wu, 2015; Wu, et al, 2015). We derive the price indices based on the released current value and constant value of the gross output and intermediate and then obtain the indices for them by single deflation. The capital and labor input indices are provided in CIP which are consistent with the KLEMS database. The reference year is 1990 and we convert them to the 2005 base year. The industries are consistent with the ISIC revision 3. However, a few industries are categorized a bit differently. We matched the classifications and use the nominal values as the weights to calculate the overall growth for the aggregated industries. Non-market economy sectors such as public services that include Housing, Public Administration and Defense, Education, Health and Social Work, Other Community, Social and Personal Services are excluded[4]. The industry classifications are listed in Table 1. The period covers from 1980 to 2010. We also add country dummies to control for different technology states between the US and China. The linkages for the industries of the US and China are extracted from the world input-output table. We use the mid-year of the sample period of 1995 to construct the spatial weight matrix.

Table 1: Industry classifications and codes

No.	Industry	ISIC Rev. 3
1	Agriculture, Hunting, Forestry and Fishing	AtB
2	Mining and Quarrying	C
3	Food , Beverages and Tobacco	15t16
4	Textiles and Textile, Leather, Leather and Footwear	17t19
5	Wood and of Wood and Cork	20
6	Pulp, Paper, Paper , Printing and Publishing	21t22
7	Coke, Refined Petroleum and Nuclear Fuel	23
8	Chemicals and Chemical	24
9	Rubber and Plastics	25

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

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; 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; Other Business Activities	71t74

International trade flows are an important medium for knowledge diffusion (Ho, et al., 2013). On the industry level, the flow of intermediate inputs is more directly related to knowledge diffusion because intermediate inputs are directly used in the production process and substantial know-how is embodied in it. The importance of trade in intermediates has long been recognized in empirical work (Grubel and Lloyd, 1975; Hummels, et al., 2001; Johnson and Noguera, 2012). We use the intermediate flow data from World input-output table to indicate the technological interdependence between industries. In the classical endogenous economic growth theory, technology progress mainly originates from "learning-by-doing". Therefore, when an upstream industry is producing intermediates for a downstream industry, the instruction and requirement of the downstream buyer will facilitate the upstream supplier to upgrade their product and improve their quality. The intermediate inputs, after taking logarithm from industry i to industry j, is denoted as $w1_{ij}$. We set the diagonal element to zero and normalize the matrix by row to obtain the spatial weight matrix denoted as $W1$. On the other hand, we also consider the spillover that may come from upstream industry by incorporating the technology embodied in the intermediate of suppliers. Therefore, by summing the transposed matrix of the input-output table with the original, we can get a symmetric spatial weight matrix that accounts for the spillover from both directions. The elements in the spatial weigh matrix are then constructed as $w2_{ij} = w1_{ij} + w1_{ji}$. The row normalized matrix is denoted as $W2$.

5 Empirical results

5.1 Estimations of Production Functions

We firstly estimate the non-spatial production function per work for the industries of both the US and China. The first column of Table 1 is based on the CSS model with time-varying fixed effects (CSSW), which is based on the standard projections used in the average production approach but with the added option to decompose the error term from the within residuals after, e.g., a fixed effects regression. The second column of Table 1 is based on the CSS model with time-varying random effects (CSSG). We also include the estimation with the sample of the industries from the US and China in the following column.

TABLE 1

Estimate of Non-spatial Cobb-Douglas Production Function

	(1)	(2)	(3)	(4)	(5)	(6)
	US+China		US		China	
Variables	CSSW	CSSG	CSSW	CSSG	CSSW	CSSG
lnk(α)	.093**	.098***	.112***	.113***	.076***	.081**
	(.021)	(.020)	(.024)	(.023)	(.029)	(.028)
lnm(β)	.529***	.541***	.174***	.170***	.582***	.594***
	(.017)	(.016)	(.022)	(.021)	(.024)	(.022)

Country-dummy	No	Yes	No	No	No	No
Intercept		-.178*		-.188*		-.298*
		(.089)		(.089)		(.145)
Time		.014***		.013***		.020**
		(.004)		(.004)		(.006)
Implied γ	.378***	.361***	.714***	.717***	.342***	.325***
	(.031)	(.029)	(.034)	(.033)	(.043)	(.040)
# of industries	44	44	22	22	22	22
# of obs.	1276	1276	638	638	638	638
HW-statistic		7.002		.603		2.361
HW- prob		.030		.740		.307

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

The coefficients of the factor inputs are all statistically significant, which represents the output elasticities of the input. The elasticities of capital, labor and intermediate are 0.093, 0.378 and 0.529 respectively in CSSW model. And the results of CSSG is close to CSSW. The time trend of productivity in the CSSG model is estimated to be 1.4%, which represents average progress of the technology of the industries of both countries during 1981-2010. We also find that the elasticities of factor inputs differ between countries. The input with the largest elasticity is labor in the US, while intermediates is the input with the largest elasticity in China. The contrast reflects their difference in growth patterns, i.e. the difference in the share of input factors in gross output. The growth rates of productivity in the US and China are 1.3% and 2% respectively in CSSG model. Hausman-Wu statistic for the fixed effects v. random effects specification of the CSS estimator for the sample includes both US and China is 7.002 with a p-value of 0.030 which weakly rejects the time-varying random effects specification on the 0.05

level. However, the statistics for the separated sample of the US or China are both small and support the random effects specification.

TABLE 2

Estimate of SDM Production Function

	(1)	(2)	(3)	(4)
	Downstream		Up+Downstream	
	CSSW	CSSG	CSSW	CSSG
lnk	.122***	.124***	.121***	.123***
	(.021)	(.020)	(.021)	(.020)
lnm	.531***	.541***	.530***	.541***
	(.017)	(.016)	(.017)	(.016)
W•lnk	-.275***	-.287***	-.249***	-.261***
	(.069)	(.065)	(.075)	(.070)
W•lnm	-.165*	-.131*	-.231**	-.187**
	(.096)	(.086)	(.097)	(.090)
Country-dummy	No	Yes	No	Yes
Intercept		-.146		-.158
		(.100)		(.102)
Time		.012**		.013**
		(.005)		(.005)
W•lny(ρ*)*	.505***	.483***	.524***	.484***
	(.058)	(.055)	(.058)	(.058)
σ_v^2	.014	.014	.014	.014
R^2	.739	.741	.732	.732
Adjusted R^2	.719	.720	.712	.711
LL	946.837	907.619	943.285	904.234
Implied γ	.348***	.335***	.349***	.336***
	(.030)	(.029)	(.030)	(.029)

Implied ϕ	-.214	-.227	-.186	-.201
Implied φ	.103	.130	.047	.075
HW-statistic		2.840		1.381
HW- prob		.725		.926

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

We conduct the Moran's I test (Cliff and Ord, 1981) against spatial autocorrelation in the error term of the non-spatial estimation. The Moran's I statistics is 0.0793, which strongly rejects the null hypothesis whatever the spatial weight matrix used. Therefore, we can infer that the traditional Solow model is mis-specified since it omits variables that reflect technological interdependence and factor input externalities. It is straightforward to show that non-spatial estimation leads to biased estimators when endogenous spatial lag variables are omitted.

Table 2 provides estimates of the SDM specified production functions based on Eq. (8). Column 1 and column 2 reflect estimates with a spatial weight matrix constructed by the downstream intermediate flow. Column 3 and column 4 are based on the spatial weight matrix constructed by the summation of downstream and upstream intermediates flows. The coefficients for capital and for intermediates are both statistically significant at the 0.1% significance level. The coefficients for the spatially lagged regressors are both significantly negative. The spatial autocorrelation coefficient ρ is positive and significant in the four columns and ranges between 0.483 and 0.524, indicating the importance of technological interdependence between industries to affect the gross output. The γ coefficient in the regression under the constant return to scale assumption ranges between 0.335 and 0.349. The other coefficients are very close among the four columns. The estimates of ϕ and φ, which represent the local spatial relationships of factor inputs, are negative and positive respectively and suggest that a sector's capital inputs have a negative effect for the productivity of another sector, while a sector's intermediate inputs have a positive effect on productivity. The Hausman-Wu statistics in the models of two spatial weight matrices suggest the random effects specification is better than fixed effects specification. Based on the random effects estimates we obtain an average time trend of 1.2% and 1.3%, which represent productivity growth in the spatial model with spatial weight matrices specified by the Downstream and Up+Downstream intermediate flows respectively. Comparing these with the result of 1.4% in the non-spatial model we can see that ignoring the spatial interactions appears to leads to an overestimation of overall productivity growth. In the following analysis of direct and indirect effects on the input factors, we choose the partial Spatial Durbin model with spatial weight matrix based on the downstream linkages as our preferred model as it has the highest log likelihood values.

5.2 The Direct and Indirect Effect of Input Factors

The output elasticities of the factor inputs in the spatial model include the direct effect of the factor inputs of the industry itself and the indirect effect of the neighbor industries' factor inputs through the sectoral linkages. Based on Eq. (9b), we obtain the (44×44) matrices Ξ_k and Ξ_m representing the direct and indirect elasticities for the input of capital and intermediates. The direct effect is the average along the diagonal elements of the matrix and the indirect effect is the average of the row (or column) sums of the off-diagonal elements. The summation of the direct and indirect effect is the average total effect. We follow the simulation process suggested by LeSage and Pace (2009) to compute the significance of these effects.

TABLE 3

Direct, indirect and total effect of input factors

SDM-Downstream		Direct		Indirect		Total	
		Effect	t-stat	Effect	t-stat	Effect	t-stat
overall	Capital	.118***	5.875	-.434***	-3.494	-.316**	-2.491
	Intermediate	.545***	34.639	.243*	1.870	.787***	5.929
	Labor	.338***	11.514	.191	.079	.529**	2.141
domestic	Capital	.119***	5.915	-.301***	-3.590	-.183**	-2.094
	Intermediate	.544***	34.663	.170*	1.864	.714***	7.575
	Labor	.337***	11.537	.133	.079	.471***	2.713
	Capital	-.001**	-2.269	-.132***	-3.123	-.133***	-3.117

international	Intermediate	.000*	1.658	.073*	1.847	.074*	1.846
	Labor	.000	.178	.057	.748	.058	.756

Notes: Significant at: *10, * *5 and * * * 1 percent; Standard error in parentheses.

The direct, indirect and total effect of each factor input in the SDM model with spatial weight matrix specified by the downstream intermediate flow is reported in Table 3. The direct effects of capital and intermediate inputs are 0.118 and 0.545 respectively and statistically significant at 1% level. The direct effect of the labor input, which is derived based on the constant return-to-scale assumption, is 0.338. The indirect effect reflects the externalities of the neighbor industries' factor inputs. The indirect effect of the capital input is negative while the indirect effects of intermediate and labor inputs are positive. The negative spillover of capital suggests that the increase of a neighbor industries' capital input may have a negative externality, which leads to the decrease of output of an industry. However, the indirect effect of intermediate and labor inputs of neighbor industries have positive externalities for the output of an industry, which suggests that the complementary relationship on labor and intermediate input outweighs the competitive relationship among industries.

To further investigate the scope and intensity of the indirect effect of a factor input, we split the indirect effect into domestic and international components based on the methods outlined in Eqs. (17)-(19). The last two groups of rows in Table 3 show the domestic and international direct, indirect and total effect of each factor input. The international direct effect is negligible, which accounts for the backflow of the knowledge diffusion through the international linkages. For the indirect effect, the international component constitutes about 30% for each factor input.

5.3 The Productivity Growth of Industries and Spillovers

The direct and indirect effect of individual productivity growth by industry, and the domestic and international spillovers of technical change through the global value chain, are shown in Table 4. Average productivity growth rates for the US and China are 1.83% and 2.95% respectively, which is approximately the same as results from the non-spatial CSS estimation for the US and for China. The average spillover from productivity growth received in the US and China is 1.83% and 2.27% respectively, which indicates that China benefits more than the US from the industrial input-output linkages. However, results from the decomposition of received spillovers into its domestic and international portions suggest that the share of domestic spillovers in the indirect effect is 76% for China's industries, which is larger than 63% for sectors in the US. Therefore, the international spillover received by China is only 0.54%, which is smaller than the 0.71% received by the US. On the other hand, from the perspective of the average spillovers of productivity growth offered, the indirect effects of the US and China are 1.65% and 2.44% respectively. The international spillovers offered by the US and China are 0.51% and 0.71% respectively, which suggest that during the past decades, the high-speed growth of China's economy has made an important contribution to the productivity growth of the economies of both countries. During the time period under study, the industries of the US and China have established a close and coordinated working relationship through the rapid development of global value chain labor division.

The sector with the fastest productivity growth in our sample is China's industry of manufacturing not elsewhere classified (NEC) and recycling (8.61%), which includes recycling, manufacture of furniture and other manufacturing that has not been categorized. Before the Chinese government issued a series of bans on solid wastes in 2017, China imported about half of the solid wastes of the world. Relying on the advantages of lower environmental costs and enormous demand for industrial raw materials such as plastics, paper and metal, the industry of recycling experienced rapid growth during our sample period. The industry with the fastest productivity growth in the US is electrical and optical equipment (7.69%), which includes the manufacture of office, accounting and computing machinery; electrical machinery and apparatus; radio, television and communication equipment and apparatus; medical, precision and optical instruments; watches and clocks. These subsectors have the highest rates of technology innovation and product enhancement. The US electrical and optical equipment sector is the most important contributor to productivity growth for both countries, with an overall spillover offered of 7.71%, the highest in our sample. Its domestic and international components are 5.17% and 2.55% and this indicates that the manufacturing of electrical and optical equipment is a very substantial driver of economic growth for both the US and China. The international spillover of China's manufacturing of electrical and optical equipment is 1.47%. Although it is the industry with second largest international spillover, there is still a big gap in technology progress compared with the counterpart in US.

TABLE 4

Technical change and spatial spillovers for SDM-Downstream model

	Direct	Received				Offered			
		Indirect			Total	Indirect			Total
		Sum	Domestic	Int'l		Sum	Domestic	Int'l	
US.s1	.0262	.0181	.0082	.0099	.0443	.0229	.0165	.0064	.0491
US.s2	.0179	.0177	.0124	.0053	.0356	.0126	.0093	.0033	.0305
US.s3	.0147	.0176	.0108	.0068	.0323	.0150	.0102	.0049	.0297
US.s4	.0169	.0195	.0108	.0087	.0364	.0149	.0103	.0047	.0318
US.s5	.0048	.0190	.0118	.0072	.0238	.0038	.0027	.0011	.0087
US.s6	.0045	.0197	.0109	.0088	.0242	.0046	.0031	.0015	.0091
US.s7	.0274	.0180	.0110	.0070	.0454	.0166	.0126	.0040	.0440
US.s8	.0112	.0201	.0098	.0103	.0313	.0114	.0079	.0035	.0226
US.s9	.0159	.0190	.0116	.0074	.0348	.0144	.0101	.0043	.0302
US.s10	.0174	.0173	.0135	.0038	.0347	.0129	.0094	.0034	.0302
US.s11	.0153	.0196	.0107	.0089	.0348	.0141	.0098	.0044	.0294
US.s12	.0106	.0193	.0102	.0091	.0299	.0097	.0065	.0032	.0203
US.s13	.0769	.0171	.0079	.0092	.0941	.0771	.0517	.0255	.1541
US.s14	.0162	.0191	.0104	.0086	.0353	.0169	.0109	.0060	.0331
US.s15	.0281	.0179	.0114	.0064	.0459	.0241	.0166	.0075	.0522
US.s16	.0140	.0173	.0138	.0035	.0313	.0086	.0066	.0020	.0226
US.s17	-.0008	.0177	.0144	.0033	.0170	-.0009	-.0006	-.0003	-.0017
US.s18	.0303	.0166	.0133	.0033	.0469	.0332	.0221	.0111	.0635
US.s19	.0118	.0175	.0131	.0044	.0293	.0120	.0082	.0038	.0239
US.s20	.0219	.0183	.0102	.0081	.0402	.0218	.0153	.0065	.0437
US.s21	.0169	.0174	.0128	.0046	.0343	.0120	.0087	.0033	.0289
US.s22	.0055	.0180	.0126	.0053	.0235	.0055	.0038	.0016	.0110
CN.s1	.0015	.0239	.0189	.0049	.0254	.0015	.0010	.0005	.0030
CN.s2	-.0168	.0244	.0194	.0050	.0076	-.0144	-.0103	-.0040	-.0312
CN.s3	.0402	.0216	.0168	.0048	.0617	.0358	.0246	.0112	.0760
CN.s4	.0417	.0223	.0152	.0071	.0640	.0395	.0272	.0123	.0813
CN.s5	.0666	.0221	.0162	.0059	.0888	.0436	.0319	.0116	.1102
CN.s6	.0447	.0225	.0167	.0059	.0672	.0359	.0252	.0107	.0806
CN.s7	.0114	.0235	.0190	.0045	.0349	.0070	.0054	.0016	.0184
CN.s8	.0482	.0226	.0165	.0061	.0707	.0459	.0318	.0142	.0941
CN.s9	.0515	.0221	.0148	.0073	.0737	.0407	.0292	.0115	.0922
CN.s10	.0485	.0218	.0158	.0060	.0703	.0442	.0317	.0125	.0927
CN.s11	.0454	.0220	.0148	.0072	.0674	.0449	.0308	.0141	.0903
CN.s12	.0569	.0215	.0153	.0062	.0784	.0501	.0356	.0145	.1070
CN.s13	.0571	.0207	.0124	.0083	.0778	.0517	.0358	.0158	.1088
CN.s14	.0670	.0213	.0158	.0055	.0883	.0527	.0376	.0151	.1197
CN.s15	.0861	.0215	.0160	.0055	.1076	.0563	.0416	.0147	.1424
CN.s16	.0054	.0240	.0196	.0044	.0294	.0037	.0028	.0009	.0092
CN.s17	.0124	.0215	.0189	.0026	.0338	.0121	.0084	.0036	.0244
CN.s18	.0001	.0254	.0228	.0027	.0256	.0001	.0001	.0000	.0003
CN.s19	-.0114	.0246	.0220	.0026	.0133	-.0081	-.0060	-.0021	-.0195
CN.s20	.0088	.0226	.0163	.0063	.0314	.0079	.0057	.0023	.0167
CN.s21	-.0016	.0249	.0219	.0030	.0232	-.0012	-.0009	-.0003	-.0028
CN.s22	-.0147	.0225	.0155	.0070	.0077	-.0123	-.0088	-.0035	-.0271

6 Simulation of US- Sino Decoupling in Global Value Chain

Based on our production function in the SDM form of Eq. (7), the logarithm of output can be expressed as follows:

$$\ln Y_{it} = \left(I - \rho \sum_{j\neq i}^{N} w_{ij} \right)^{-1} (\Omega_i + \delta_i t + v_{it} + \phi \sum_{j\neq i}^{N} w_{ij} \ln k_{jt} + \varphi \sum_{j\neq i}^{N} w_{ij} \ln m_{jt}) + \alpha \ln k_{it} + \beta \ln m_{it} + \ln L_{it}$$

$$= \left(I - \rho \sum_{j\neq i}^{N} w_{ij} \right)^{-1} \times$$

$$\left[\Omega_i + \delta_i t + v_{it} + \alpha \ln k_{it} + \beta \ln m_{it} + (\phi - \rho\alpha) \sum_{j\neq i}^{N} w_{ij} \ln k_{jt} + (\varphi - \rho\beta) \sum_{j\neq i}^{N} w_{ij} \ln m_{jt} + \left(I - \rho \sum_{j\neq i}^{N} w_{ij} \right) \ln L_{it} \right]. \tag{22}$$

Individual productivity growth and relative output elasticities of factors inputs are fixed in our simulations. Replacing the term in brackets with Θ_{ij}, Eq. (22) can be written more compactly as:

$$\ln Y_{it} = \left(I - \rho \sum_{j\neq i}^{N} w_{ij} \right)^{-1} \Theta_{it}. \tag{23}$$

Following the methods in decomposing the domestic effect and international effect that we have outlined above, we can simulate the output change based on varying scenarios of US-Sino decoupling of their value chain. By splitting the spatial weight matrix into the domestic and international block matrices, we simulate the impact of different degrees of international supply chain disruptions on the gross output of industries in both countries. We consider four different scenarios of supply chain disruptions: a 10%, 20%, 50% and 100% reduction of international intermediate inputs flows with the domestic intermediate flow left unaffected. The spatial weight matrix is replaced by a new one constructed with reduced international linkages based on the four different scenarios. We then calculate $\tilde{Y}_{it}$ as the output generated from the spatial multiplier based on the reduced international linkages. By taking the average of $\left(Y_{it} - \tilde{Y}_{it}\right) / Y_{it}$ for all the years, we can obtain the output declines due to the four levels of supply chain disruptions. These are shown in Table 5. The first scenario of a 10% reduction of international intermediate flow for example, indicates an average output decline of 5.5% for US industries and 7.0% for Chinese industries. The sector with the steepest drop is China's electrical and optical equipment sector, which shows a decrease of 10.3%. However, the industry that may be the most seriously affected in the US is agriculture, hunting, forestry and fishing, which shows a decrease of 8.2%. The greater reduction in intermediate trade flow, the greater impact will be received on the output of both industries. In the extreme case of complete closure of bilateral trade between the US and China, the average output decline is 37.0% for US and 46.7% for China.

TABLE 5
Percentage of output decline on different level of supply chain disruptions

	-10%		-20%		-50%		-100%	
	US	CN	US	CN	US	CN	US	CN
s1	8.2%	6.9%	15.5%	13.1%	32.8%	28.6%	51.4%	46.9%
s2	4.3%	6.4%	8.2%	12.3%	18.2%	27.1%	30.5%	45.0%
s3	6.3%	6.3%	12.0%	12.0%	26.0%	26.5%	42.4%	44.0%
s4	6.5%	9.2%	12.4%	17.2%	26.6%	36.5%	42.8%	57.5%
s5	5.2%	7.8%	9.9%	14.9%	21.8%	32.1%	36.0%	51.8%
s6	6.7%	7.7%	12.8%	14.6%	27.4%	31.7%	43.9%	51.2%
s7	5.8%	5.8%	11.0%	11.2%	23.9%	24.8%	39.1%	41.5%
s8	7.8%	7.8%	14.8%	14.7%	31.3%	31.8%	49.1%	51.2%
s9	5.6%	9.3%	10.6%	17.6%	23.1%	37.1%	37.7%	58.2%
s10	3.1%	7.8%	5.9%	14.8%	13.3%	31.9%	22.9%	51.5%
s11	6.7%	9.3%	12.7%	17.4%	27.2%	36.9%	43.7%	57.9%
s12	7.3%	8.0%	13.8%	15.2%	29.4%	32.8%	46.8%	52.6%
s13	7.7%	10.3%	14.6%	19.3%	31.0%	40.2%	48.8%	61.9%
s14	6.9%	7.1%	13.1%	13.5%	28.2%	29.3%	45.0%	48.0%
s15	5.2%	7.1%	9.9%	13.6%	21.7%	29.7%	35.7%	48.5%
s16	2.9%	5.7%	5.5%	10.9%	12.6%	24.3%	21.7%	40.8%

s17	2.7%	3.4%	5.2%	6.5%	11.8%	14.9%	20.5%	26.3%
s18	2.7%	3.5%	5.3%	6.7%	12.1%	15.4%	20.9%	27.1%
s19	3.7%	3.4%	7.0%	6.7%	15.8%	15.3%	26.9%	26.9%
s20	6.9%	8.1%	13.0%	15.4%	28.0%	33.0%	44.9%	53.0%
s21	4.0%	3.9%	7.6%	7.6%	17.1%	17.3%	29.0%	30.1%
s22	4.7%	8.8%	9.0%	16.6%	20.0%	35.3%	33.5%	56.0%
Avg	5.5%	7.0%	10.4%	13.3%	22.7%	28.7%	37.0%	46.7%

7 Conclusion

In this paper, we propose a production model with heterogeneous productivity growth and spatial interdependence under the GVCs labor division system for industries in the US and China. We estimate the output elasticity of capital, labor and intermediate inputs by the direct and indirect effect with modified spatial Durbin model. We also measure the individual productivity growth of the industries and their spillovers through input-output linkages. We further develop a method to decompose the spillovers of factor inputs and productivity growth into domestic and international spillovers.

Our study includes 44 industries in the US and China from 1981 to 2010. The SDM model with a spatial weight matrix based on downstream intermediate linkages is our preferred model. Our results suggest that the indirect effects of factor inputs are significant and play an important role in both economies. International spillovers between both countries account for about 30% of the indirect effect for each factor. The spillovers from productivity growth received by the industries of the US and China average about 1.83% and 2.27%, while a greater proportion of China's spillover received is dependent on its domestic industrial linkage. International spillovers offered by the industries of the US and China are 0.51% and 0.71%, which suggests the close interdependent relationship between these industries.

We also simulate the possible scenarios of decoupling between the US and China with our model for four different levels in the reduction of international intermediate input flows. Results suggest average output declines of 5.5% in US and 7.0% in China when the international intermediate trade drops by 10%. Were trade totally cut off, the US would suffer a 37.0% drop in output and China would suffer a 46.7% decline. The relationship between the industries of both countries is more complementary than competitive. Our results suggest that the trade frictions and other “decoupling” policies between the US and China will lead to a lose-lose situation for both sides.

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