Productivity Growth and Spillover across European Industries: A Global Value Chain Perspective Based on EURO KLEMS

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ABSTRACT

The development of production networks has promoted knowledge flows and technology diffusion among industries over the past decades, which affects the productivity growth for most countries. This paper examines productivity growth in the presence of inter-sectoral linkages. We construct a spatial production model with technological spillovers and productivity growth heterogeneity at the industry-level. We use the global value chain (GVC) linkages from inter-country input-output tables to model the technological interdependence among industries, and estimate total factor productivity (TFP) growth and its spillover among European countries. We find that the spillover effects from intermediate inputs is significant. There is a network effect of TFP growth from one country to another through input-output linkages. Our paper provides a better understanding of the impact of spillover effects on TFP growth in the context of GVCs.

Keywords: TFP growth, global value chain, World KLEMS, EU productivity, spatial-stochastic frontier

JEL Classification: C23, C67, O47

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1. Introduction

The allocation of resource use within the global value chain (GVC) is one of the more drivers of global economic growth in recent decades, connecting the industrial systems of various countries into a global production network. As goods and services production is increasingly fragmented, the growth of one country may be more dependent on the growth of other countries than in the past. Technology improvements in one industry may be transmitted to all industries in the production network through the input-output linkages.

The economic integration in Europe and progress in the "European Single Market" has facilitated the movement of goods, services, capital and people among member states of European Union and has enabled member states to concentrate on a specific product or even a segment or component in the supply chain. The development of production networks across countries in this region contributes to the optimization of spatial allocation of resources and thus contributes to country and to world productivity growth.

Figure 1 displays the inter-sectoral network across countries in the European area (as in Panel A and Panel C) based on the input-output linkages with a threshold of 2.5% for the percentage of the intermediate input in total intermediate purchased by each sector in the World Input-Output tables.[1] Panel D is the inter-sectoral network diagram of the US-Asia Pacific area with the same threshold value for comparison.[2] International linkages among European countries are much denser than that among the Asian countries in our sample, which suggests that although Asia is the global manufacturing center, the production network is mainly concentrated within their national borders, whereas the European countries are more successful in the development of international value chain co-operations. Panel A and Panel C of Figure 1suggest the different positions of European countries in the network and its evolution over time. Germany is shown to be a regional supply hub, with the most extensive international downstream linkages to the industries in other Euro countries, which suggest it has the broadest range of customers in Europe during our sample period 2000 to 2014. Belgium had the largest number of international suppliers in Europe in 2000. However, this position was replaced by Austria in 2014. The variation of relative position of countries in the network

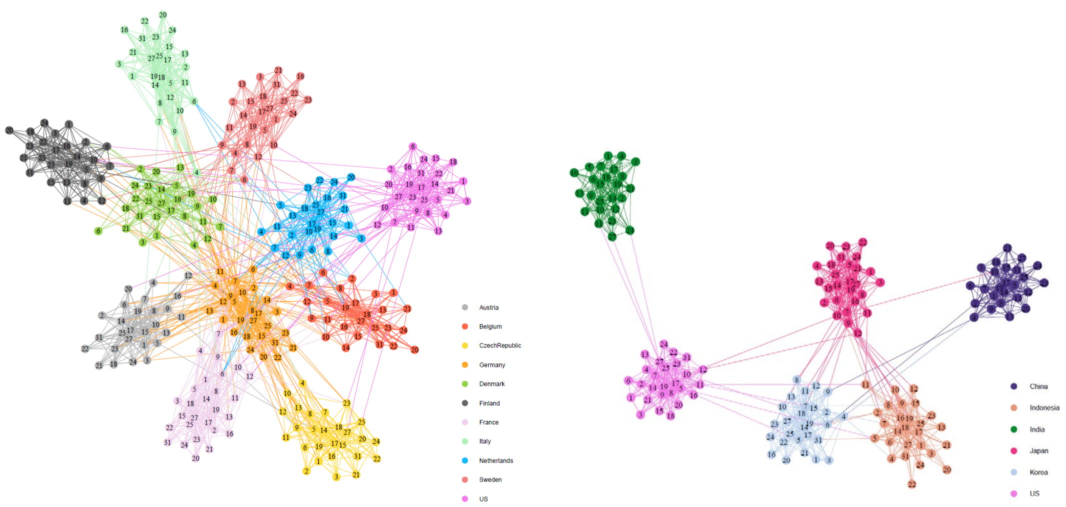
[1] The European countries include Austria, Belgium, the Czech Republic, Germany, Denmark, Finland, France, Italy, the Netherlands and Sweden, which along with the US are the foci of productivity analyses in this paper.

[2] The countries whose networks are displayed for the Asia & Pacific area include China, Indonesia, India, Japan and Korea.

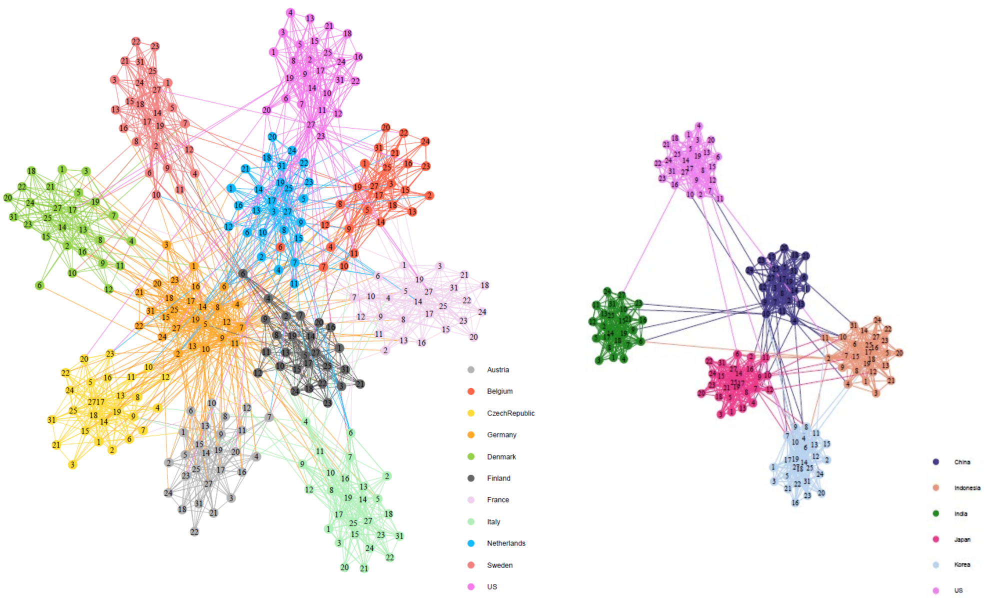
implies the changes in the pattern of supply chain across European countries. The total number of international linkages among the 297 industries of the ten European economies and the United States increased by one-third from 290 in 2000 to 384 in 2014, while the total number of domestic linkages declined by 8.3 per cent (from 2447 in 2000 to 2244 in 2014). This suggests that the European countries are integrating their economies and thus becoming more interdependent through the growing cross-country inter-sectoral linkages. In contrast, the total number of international linkages among the 162 industries of the five major economies in the Asia-Pacific area as well as the United States only increased by 21.6 per cent (from 37 to 45), while the number of domestic linkages rose 1.8 per cent (from 1422 to 1447), as shown in Panel B and Panel D in Figure 1. The increasingly integrated European value chains offer more opportunities for these countries to appropriate advanced frontier technologies and thus promote total factor productivity (TFP) growth. Nevertheless, the spillover effects from input-output linkages are not considered in most empirical studies on productivity measurement. In this paper, we explore the transmission channels of technology spillovers and empirically examine the impact of such spillovers on TFP growth, as a complement to the existing literature.

Figure 1: Intersectoral network corresponding to the World Input-output tables.

Panel A: Network of EU-10 and the US in 2000 **Panel B: Network of Asia-Pacific and the US in 2000**



Panel C: Network of EU-10 and the US in 2014 **Panel D: Network of Asia-Pacific and the US in 2014**



Notes: For every input transaction above 2.5% of the total input purchases of a sector, a link is drawn between that sector and the input supplier.

Our work is related to two strands of the literature. The first is a growing literature investigating the relationship between productivity growth and participation in the global value chain. Timmer *et al.* (2014) summarized the effects of global value chains on industry productivity growth through input-output linkages. Halpern, Koren and Szeidl (2015) used a structural model to explore the impact of imported inputs on productivity. Dhyne and Duprez (2017) examined the participation of global and local value chains and its implication for the efficiency level in Belgian firms. Lu *et al.* (2018) found that there is a positive relationship between firm foreign value-added ratio (FVAR) and productivity. Timmer and Ye (2020) used the growth accounting framework to analyze factor inputs and TFP growth in GVCs. However, most of these studies assumed that the production technology of industries or firms are independent and did not consider possible interdependencies in the production network. We differ from this literature by incorporating the spillover effect of production processes, focusing on the impact of the network effect from factor inputs and technology on TFP growth in the context of GVCs.

Our research also relates to studies that investigate the impact of technological spillovers in the form of patents as well as spillovers from product competition on productivity growth. Bloom, Schankerman and Van Reenen (2013) and Lucking, Bloom and Van Reenen (2019) discussed two types of spillovers: knowledge spillovers in the technology space and product market rivalry in the product market space. Their studies are focused on the spillovers among firms that use patenting in similar technological areas that sell products in the same market. Griliches (1979) discussed another kind of spillover that affects productivity improvement in an industry (say industry *i*) by purchasing intermediates from another industry, to the extent that the productivity improvements in the other industry have not been appropriated by its producers and not been incorporated in the official price indices of industry *i* by the relevant statistical agencies, referred to as "rent spillover." Our study differs from Feenstra et al. (2013) and Feenstra, Inklaar and Timmer (2015), who measured productivity growth by the Tornqvist index using a growth accounting framework based on the residual of output growth and total input growth. We estimate TFP growth using econometric procedures which allow us to estimate sectoral productivity with flexibility in the specification of the spatial production function. The empirical specification of technology spillovers in this paper differs from several previous studies. First, while Ho, Wang and Yu (2018), among others, argued that a spatial weight matrix based on international trade flows could capture multi-country technological interactions, we believe that using intermediate flows as the interaction matrix is more appropriate. The role of intermediate flows as a channel for shock propagations has been investigated in recent studies of production networks (Acemoglu et al., 2012; Acemoglu, Akcigit and Kerr, 2016; Autor and Salomons, 2018; Carvalho and Tahbaz-Salehi, 2019; Bigio and La'O, 2020). This is because as, an important vector of knowledge diffusion, intermediate flows better represent and reflect communication and cooperation in production among industries. Second, several studies in this literature are based on the assumption of homogeneity in productivity growth across industries (Ertur and Koch, 2007; Liu and Cheng, 2021). Due to the technical and economic features of each sector, the specification of homogenous parameters when modeling economic growth may be inaccurate, as was shown by Durlauf (2001). Therefore, we use a flexible spatial Cobb-Douglas production function and a parameter identification empirical methodology based on a spatial time-varying stochastic frontier, which allows for the heterogeneous technological progress and technology spillovers at the industry level. Furthermore, unlike the imposed distribution assumptions in Glass, Kenjegalieva and Sickles (2016), we combine the spatial econometrics with the previous work of Cornwell, Schmidt and Sickles (1990) for estimation, which does not require further parametric assumptions on the distribution of the inefficiency term. Furthermore, a few recent papers are more closely related to our work. Liu and Sickles (2021) combines the methodology of spatial econometrics model and time-varying stochastic frontier to estimate the industry-specific productivity and spillovers within the Asia-Pacific value chain. Following this method, Liu, Sickles and Zhao (2022) estimates the technology spillover between the US and China and evaluates the impact of simulated US-Sino trade Decoupling scenarios. Although the estimation technique is related to ours, both papers assume a linear technology progress and only measure the gross spillover received or offered by industry. Our analysis considers the non-linear technology progress which is more consistent with the global trend of slowdown in TFP growth and investigates the spillover from a more detailed network perspective that distinguishes the source and destination of spillover effect by countries.

The main contribution of the paper is to investigate the TFP growth and spillover in European countries with a spatial econometric model with heterogeneous technology progress. Firstly, we extend the Cobb-Douglas production function with technology spillover incorporated, in which the parameters can be empirically estimated and used to measure industry TFP growth with interdependence. Secondly, we investigate the TFP growth of ten EU countries over the period 2000-2014, and find the correlations between industry TFP growth and GVC participation. Thirdly, we estimate the network effect of TFP growth for manufacturing sectors of EU countries, based on which we further decompose the network effect into a domestic and international component.

The remainder of our paper is organized as follows. In the next section we introduce our model specification and methodology for examining the spillover effect of factor inputs as well as TFP growth. Section 3 describes our data and reports descriptive statistics. Section 4 presents our empirical results with the spatial production function. Section 5 focuses on the TFP growth for European economies. Section 6 illustrates the spillover effect of TFP growth using the matrix of marginal output. Section 7 concludes.

2. Model

In this section, we present our spatial production model to allow interdependence in production and heterogeneity in productivity growth at the industry-level. We then derive output elasticities for the input factors using the matrix of partial derivatives of output with respect to the corresponding factor. We use these measures to examine the spillover effects of factor inputs and TFP growth.

2.1 Interdependent industrial production function

Consider the production network consisting of N industries, where each industry's production function can be represented by a Cobb–Douglas function that exhibits constant returns to scale in capital, labor and intermediate inputs. Then, for industry i at time t, we have:

$$Y_{it} = A_i(t) K_{it}{}^{\alpha} M_{it}{}^{\beta} L_{it}{}^{1-\alpha-\beta}, \quad i=1,\ldots,N; \quad t=1,\ldots,T,$$

where Y_{it} is total output, K_{it}, M_{it} and L_{it} are the capital, intermediates, and labor used in industry i, with a, β and $1-\alpha-\beta$ as the factor output elasticity, respectively. $A_i(t)$ is the industry-level TFP and is time specific and industry specific. Therefore, output per worker can be written as:

$$y_{it} = \frac{Y_{it}}{L_{it}} = A_i(t)(\frac{K_{it}}{L_{it}})^{\alpha}(\frac{M_{it}}{L_{it}})^{\beta}(\frac{L_{it}}{L_{it}})^{1-\alpha-\beta} = A_i(t) k_{it}^{\alpha} m_{it}^{\beta} \tag{1}$$

where y_{it}, k_{it} and m_{it} are output per worker, capital per worker and intermediate per worker, respectively. Due to technological interdependence among industries, the productivity level $A_i(t)$ is given by:

$$A_i(t) = \Omega_i(t) \prod_{j \neq i}^{N} A_j(t)^{\rho w_{ij}} \prod_{j \neq i}^{N} k_{jt}{}^{\phi w_{ij}} \prod_{j \neq i}^{N} m_{jt}{}^{\varphi w_{ij}}. \tag{2}$$

In equation (2), the productivity level of industry i contains three major components. First, a proportion of technological change is exogenous and Hick-neutral, which varies both over industries and over time, given by $\Omega_i(t) = \Omega_i(0) e^{R_i(t)+v_{it}}$, where $\Omega_i(0)$ denotes the initial technology level of industry i, and $R_i(t) = \delta_{1i} t + \delta_{2i} t^2$ is a quadratic function approximating the time-varying component, v_{it} is the approximation error for the level of technology. Second, technical progress of industry i is assumed to be affected by technological advances in neighboring industry j, and this effect depends on the strength of interdependence between industry i and industry j, which we denote as w_{ij}. Third, following the Arrow-Romer's physical capital externalities (Arrow,1962; Romer, 1986), capital deepening in neighboring industries may increase the total capital stock in the society, in which case the economy will accumulate knowledge and bring productivity gains to the industry in question. Similarly, according to studies on vertical specialization and off-shoring (Grossman and Rossi-Hansberg, 2008; Baldwin and Robert-Nicoud, 2014), an increase in the intermediate input per worker of its upstream suppliers or downstream customers can promote productivity growth due to a deepening in the division and specialization of the production network (denoted as intermediate deepening).

We can resolve equation (2) for $A_i(t)$,[3] substitute $A_i(t)$ into the production function (1), and express the logarithm of output per worker in matrix form as:

$$\begin{aligned}\ln\, y &= \rho\left(W\otimes I_T\right)\ln y+\alpha\ln k+\beta\ln m+\Gamma_0+\Gamma_1 t+\Gamma_2 t^2+v \\ &+(\phi-\alpha\rho)\left(W\otimes I_T\right)\ln k+\left(\varphi-\beta\rho\right)\left(W\otimes I_T\right)\ln m\end{aligned}, \tag{3}$$

where y, k, m and v are $NT\times 1$ vectors, W is a $N\times N$ spatial weights matrix, $\Gamma_0=\ln\Omega_i(0)\otimes\iota_T$, $\Gamma_1=\delta_{1i}\otimes\iota_T$, $\Gamma_2=\delta_{2i}\otimes\iota_T$, ι_T is the T dimensional vector of ones. It is this Spatial Durbin Model (SDM) that we will use for our estimations.

2.2 Spillover of factor inputs

Due to the interdependence of production, the usual interpretation of a and β as output elasticities is invalid for the spillover effect of factor inputs. Taking the output elasticity of capital for example, the variation of output is not only affected by the change in an industry's own capital input, but also by the change of neighboring industries' capital inputs. Therefore, we compute direct and indirect elasticities using the approach proposed by LeSage and Pace (2009). Then the matrix of partial derivatives of output per worker y, with respect to per worker capital k, in industry $1\sim N$ and in period t is written as:

$$E_k\equiv\left[\frac{\partial\ln y}{\partial\ln k_1},\frac{\partial\ln y}{\partial\ln k_2},\cdots,\frac{\partial\ln y}{\partial\ln k_N}\right]_t=\begin{bmatrix}\frac{\partial\ln y_1}{\partial\ln k_1} & \frac{\partial\ln y_1}{\partial\ln k_2} & \cdots & \frac{\partial\ln y_1}{\partial\ln k_N}\\ \frac{\partial\ln y_2}{\partial\ln k_1} & \frac{\partial\ln y_2}{\partial\ln k_2} & \cdots & \frac{\partial\ln y_2}{\partial\ln k_N}\\ \vdots & \vdots & \ddots & \vdots\\ \frac{\partial\ln y_N}{\partial\ln k_1} & \frac{\partial\ln y_N}{\partial\ln k_2} & \cdots & \frac{\partial\ln y_N}{\partial\ln k_N}\end{bmatrix}_t \tag{4a}$$

$$=\left(I_N-\rho W_N\right)^{-1}\begin{bmatrix}\alpha & w_{12}\left(\phi-\alpha\rho\right) & \cdots & w_{1N}\left(\phi-\alpha\rho\right)\\ w_{21}\left(\phi-\alpha\rho\right) & \alpha & \cdots & w_{2N}\left(\phi-\alpha\rho\right)\\ \vdots & \vdots & \ddots & \vdots\\ w_{N1}\left(\phi-\alpha\rho\right) & w_{N2}\left(\phi-\alpha\rho\right) & \cdots & \alpha\end{bmatrix}. \tag{4b}$$

Then the mean output elasticity of own capital input for all industries can be measured by the average of the diagonal elements of the matrix derived from equation (4b), representing the percentage change of an industry output per worker due to a percentage increase in its own capital per worker. Note that these own effects include the feedback effects that arise as a result of effects passing through neighboring industries and back to the industries themselves via the input-output

[3] More details are presented in the Appendix A.

linkages. The mean output elasticity of neighboring industries' capital input, which we denoted as network effect, is the average column sum of the off-diagonal elements in the matrix derived from equation (4b), which represents the impact of a percentage change in an industry's capital per worker on the output per worker of all other industries. The mean overall effect of capital, reflecting the average impact of changing a percentage of capital per worker to the output per worker of all industries in the production network, is measured by the sum of the own effect and the network effect. Similarly, we can derive the own, network and overall effect of intermediate inputs. In the global value chain setting, we can further decompose the network effect into a domestic network effect coming from domestic inter-industry linkages and an international network effect coming from industrial linkages across countries, based on the information provided in the world input-output tables (Liu and Cheng, 2021).

2.3 TFP growth and spillover in EU

Differentiating equation (3) with respect to the time trend in period t, we obtain the spillover effects of technical progress:

$$g_t \equiv \left[\frac{\partial \ln y}{\partial t}\right] = \left(I_N - \rho W\right)^{-1} \begin{bmatrix} R_1(t)' & 0 & \cdots & 0 \\ 0 & R_2(t)' & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & R_N(t)' \end{bmatrix} = \begin{bmatrix} \tilde{w}_{11}R_1(t)' & \tilde{w}_{12}R_2(t)' & \cdots & \tilde{w}_{1N}R_N(t)' \\ \tilde{w}_{21}R_1(t)' & \tilde{w}_{22}R_2(t)' & \cdots & \tilde{w}_{2N}R_N(t)' \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}_{N1}R_1(t)' & \tilde{w}_{N2}R_2(t)' & \cdots & \tilde{w}_{NN}R_N(t)' \end{bmatrix}, \quad (5)$$

where $R_i(t)' = \partial R_i(t) / \partial t = \delta_{1i} + 2\delta_{2i}t$ is the independent TFP growth of industry i, $\tilde{w}_{ij}$ is the (i, j) th element of $\left(I_N - \rho W\right)^{-1}$. In the diagonal element of the matrix in equation (5) is the own effect g_t^{own}, representing the productivity change of industry itself at time t. The off-diagonal element of the matrix is the network effect $g_t^{network}$, which corresponds to the spillover effect of TFP growth from neighboring industries. For example, $\tilde{w}_{21}R_1(t)'$ represents the productivity change attributed to the spillover that originate from industry 1 and received by industry 2. Therefore, the index of rows denotes the industry of spillover receiving and the index of columns denotes the industry of spillover offering. Furthermore, assuming there are s countries in the production network and q industries in each country, by partitioning the matrix of $g_t^{network}$ into block matrices, we can rewrite $g_t^{network}$ to decompose the spillover transmitted domestically and internationally as:

$$\boldsymbol{g}_t^{network} = \begin{bmatrix} 0 & \tilde{w}_{12}R_2(t)' & \cdots & \tilde{w}_{1N}R_N(t)' \\ \tilde{w}_{21}R_1(t)' & 0 & \cdots & \tilde{w}_{2N}R_N(t)' \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{w}_{N1}R_1(t)' & \tilde{w}_{N2}R_2(t)' & \cdots & 0 \end{bmatrix} = \begin{bmatrix} \overset{\sim 11}{\boldsymbol{g}_t} & \overset{\sim 12}{\boldsymbol{g}_t} & \cdots & \overset{\sim 1s}{\boldsymbol{g}_t} \\ \overset{\sim 21}{\boldsymbol{g}_t} & \overset{\sim 22}{\boldsymbol{g}_t} & \cdots & \overset{\sim 2s}{\boldsymbol{g}_t} \\ \vdots & \vdots & \ddots & \vdots \\ \overset{\sim s1}{\boldsymbol{g}_t} & \overset{\sim s2}{\boldsymbol{g}_t} & \cdots & \overset{\sim ss}{\boldsymbol{g}_t} \end{bmatrix}, \tag{6}$$

where $\overset{\sim ij}{\boldsymbol{g}_t}$ is a $q \times q$ submatrix of $g_t^{network}$. The submatrices in main block diagonal $\overset{\sim ii}{\boldsymbol{g}_t}$ denotes the spillover of productivity growth within country i. The submatrices in off-diagonal $\overset{\sim ij}{\boldsymbol{g}_t}$ represents that the spillover of productivity change across borders goes from country j to country i (e.g. $\overset{\sim 12}{g_t}$ represents the spillover from country 2 to country 1).

3. Data

We draw our data from the EU KLEMS dataset. The 2017 release of EU KLEMS Growth and Productivity Accounts provides the data on factor inputs and gross output for all 28 member states of the European Union and the United States. We extract a panel comprising 10 European economies, including Austria, Belgium, the Czech Republic, Germany, Denmark, Finland, France, Italy, the Netherlands and Sweden, over the period of 2000-2014.[4] These 10 countries accounted for about 80 percent of European Union GDP in each year of the sample period,[5] which is representative of the complex production network among the EU countries. In addition, we included the United States in our sample for comparisons of TFP growth between the US and Europe. Since the main purpose of our study is to investigate productivity growth and spillovers in a context of GVC, we omitted the non-market economy industries of these countries.[6] We calculate the volume indices for gross output and intermediate inputs using 2010 as the base year. Capital services and labor services volume indices are directly obtained from the growth accounting. We also use the quantities of input and output variables to verify the robustness of empirical findings. Real gross output and real intermediate inputs are measured by the corresponding nominal values divided by the price indices which are provided by Socio Economic Accounts (SEA) from the World Input-Output Database (WIOD). The real capital stock is measured by using the nominal values provided by EU KLEMS

[4]Although the latest EU KLEMS Growth and Productivity Accounts up to the 2019 release can be accessed, gross output and intermediate inputs related variables are missing post-2015 for some countries. In addition, WIOD database provides data of input-output linkages used in the section below covers the period of 2000-2014, therefore our sample centers on 2000-2014 when both data sources are available.
[5]Data sources: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD
[6]Our sample excludes the Real Estate Activities, Community Social and Personal Services, Other Service Activities, Activities of Households.

and the capital price indices derived from the PWT version 9.1 (Feenstra et al., 2015). The capital stock in the WIOD is in nominal values and we use the price index from the PWT as the deflator. However, the price index from the PWT is at the national level and thus that the deflators for each industry are same within each country. Summary statistics of these variables are reported in Table 1.

Table 1: Variable definitions and summary statistics

	Variable	Obs	Mean	Std. Dev.	Min	Max
Real Variables	$\ln y$	3,945	10.49	1.52	6.51	14.89
	$\ln k$	3,945	10.04	1.58	5.82	14.53
	$\ln l$	3,945	4.97	1.65	0.00	10.00
	$\ln m$	3,945	9.93	1.53	6.04	13.95
Index Variables	y_{QI}	3,945	99.48	15.85	26.63	253.03
	k_{QI}	3,945	96.03	25.07	28.31	831.52
	l_{QI}	3,945	104.00	14.63	61.53	219.82
	m_{QI}	3,945	100.02	18.85	26.49	294.70

We use the flows of intermediate goods between industries provided by WIOD to construct the spatial weights matrices. In order to match the industries from EU KLEMS with the industries from WIOD, we aggregate some of them and obtain 27 industries in each country (Appendix Table A.1). We extract industry international input–output linkages among these industries from the world input-output table for the period from 2000 to 2014, and use averages of the intermediate flows over this time as the weights to address potential endogeneity problems that might arise were we to use time-varying weights (Cohen and Paul, 2004; Ertur and Koch, 2011). The spatial weight matrix W_{supply} is constructed using the transpose of the input-output matrix and the elements on main diagonal are set to zero. In order to reflect the technology spillover in the production network, W_{supply} is row normalized, so that its element w_{ij} captures the share of the upstream industry j 's product in the total intermediate consumption of the downstream industry i. which is consistent with the direction of technology spillovers from upstream industries to downstream industries as discussed in Acemoglu et al. (2012), Acemoglu, Akcigit and Kerr (2016), Autor and Salomons (2018). We also consider the interaction matrices W_{demand} and $W_{transaction}$ to check the robustness of our results. W_{demand} is obtained by the original input-output matrix, where its element w_{ij} represents the share of intermediate inputs from upstream industry i to downstream industry j, and this channel of spillovers is consistent with the spillovers of “learning-by-doing”. We add the original and transposed matrix of the input-output table together to construct the spatial weights $W_{transaction}$, where its element w_{ij} represents two-way intermediate flows between i industry and j.

4. Empirical results

4.1 Estimations of industrial Production Functions

In Table 2 we report the estimation results of the SDM specified production functions based on Eq. (3). We use both output per capita index and real per capita output for the dependent variables. The EU KLEMS database provides both the gross output growth index (year 2010=100) and real output. We provide results for both to check for any substantive differences and to examine the robustness of our findings across these different output measures. The gross index numbers utilize gross output (Y), capital service (K), labor service (L) and intermediate input (M) from the EU KLEMS. Columns 1–6 of Table 2 report empirical results based on three weighting matrices W_{supply} , W_{demand} and $W_{transaction}$. More specifically, columns 1, 3 and 5 are the empirical results specified by the spatial weight matrix of W_{supply} , W_{demand} and $W_{transaction}$ respectively, with the Time-varying fixed effect (T-VFE) and columns 2, 4 and 6 are the corresponding empirical results with the Time-varying random effect (T-VRE). Estimates of the coefficient ρ of the spatially lagged dependent variable range between 0.1970 and 0.2990 for these three specifications of the weighting matrix and are statistically significant at the 0.1% level, suggesting positive network effects in production among the industries in our study. Given the similarity of results based on these three weighting matrix specifications, we will discuss results for the matrix W_{supply}.[7] The real value data is based on traditional input indicators, i.e., the capital stock and number of employees, which come from the WIOD database. From Column 7-8 of Table 2 we can see that the estimation results for the real variables and volume indices reported in Columns 1–2 are quite comparable and we focus our discussion below on results based on volume indices.[8] As shown in the first two

[7] We choose the result of the estimation with the spatial weight matrix of W_{supply} to disscuss in detail since a number of recent papers show that the supply-side intermediate linkage from upstream suppliers to downstream customers is a major channel of TFP spillovers (Acemoglu et al. ,2012; Acemoglu, Akcigit and Kerr ,2016; Autor and Salomons, 2018).

[8] The reason is that the index for capital input is capital services instead of the capital stock, wherein the former considers the user cost of the asset. And the index of labor input is labor service, which takes into account the contribution of skill levels of different workers.

Columns of Table 2, coefficients on capital and intermediate are both significant and positive in all estimations. It is important to note that these parameters in the spatial Durbin model cannot represent the output elasticities of the factor inputs (LeSage and Pace, 2009). We should use the direct and indirect effects estimates derived from Eq. (4b), which will be fully explained in Section 4.2. The coefficients on $Time$ and $Time^2$ representing the average Hicks-neutral technological change of industries are positive in first order and negative in second order, which implies that technical progress is represented as an inverted-U curve. This is consistent with the trend of TFP growth slowdown in Europe as discussed in several previous studies (Feenstra et al., 2015; van Ark and Jäger, 2017; Gordon and Sayed, 2019). The model specifications using Time-varying FE and Time-varying RE model are the same. The Hausman-Wu statistic for the time-varying fixed effects v. time-varying random effects specification has a p-value of 0.00 and we thus focus the remainder of our discussion of results based on the time-varying fixed effects specification.

Table 2: Estimates SDM Production Functions

parm	Index Variables						Real Variables	
	W_{supply}		W_{demand}		$W_{transaction}$		W_{supply}	
	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE	T-VFE	T-VRE
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
lnk	0.0643***	0.0699***	0.0702***	0.0736***	0.0697***	0.0736***	0.1502***	0.1615***
	(0.0084)	(0.0073)	(0.0084)	(0.0072)	(0.0084)	(0.0073)	(0.0119)	(0.0093)
lnm	0.5540***	0.5697***	0.5510***	0.5679***	0.5500***	0.5668***	0.5742***	0.6063***
	(0.0081)	(0.0074)	(0.0081)	(0.0074)	(0.0081)	(0.0075)	(0.0080)	(0.0071)
W•lnk	-0.0384	-0.0543**	-0.0833***	-0.0770***	-0.0792**	-0.0800***	-0.1620***	-0.1640***
	(0.0259)	(0.0178)	(0.0228)	(0.0162)	(0.0256)	(0.0175)	(0.0149)	(0.0117)
W•lnm	0.0444	0.0030	0.0631	0.0707*	0.0932**	0.0820*	0.0535	0.0002
	(0.0312)	(0.0295)	(0.0323)	(0.0312)	(0.0337)	(0.0322)	(0.0310)	(0.0295)
Country-dummy	no	yes	no	yes	no	yes	no	yes
Year-dummy	yes	yes	yes	yes	yes	yes	yes	yes
W•lny(ρ)	0.2680***	0.2990***	0.2251***	0.1970***	0.2161***	0.2061***	0.3080***	0.3080***
	(0.0337)	(0.0319)	(0.0348)	(0.0339)	(0.0351)	(0.0342)	(0.0323)	(0.0318)
σ_v^2	0.0006	0.0006	0.0006	0.0006	0.0006	0.0006	0.0007	0.0007
LL	9273	8886	9279	8891	9280	8892	9184	8813
R^2	0.6904	0.6943	0.6919	0.6964	0.6927	0.6967	0.9091	0.9267
Adjusted R^2	0.6118	0.6150	0.6136	0.6177	0.6147	0.6180	0.8860	0.9077

Number of obs	3945	3945	3945	3945	3945	3945	3945	3945

Notes: "T-VFE" is Time-varying FE and denotes spatial CSS model (Cornwell, et al., 1990) with Fixed Effect, and "T-VRE" is time-varying RE and denotes spatial CSS model with Random Effects. "LL" denotes the loglikelihood. Significant at: *5, * *1 and * * * 0.1 percent. The individual coefficients of δ_{1i} and δ_{2i} are not show in this table due to the excessive quantities.

4.2 Spillover of input factors

The first two rows of Table 3 show the estimated overall direct, indirect and total output elasticity of factor inputs. The direct elasticity is calculated by the mean of the diagonal entries of the matrix derived from Equation (4b) and the indirect elasticity is computed by the mean of the row sums of off-diagonal entries. We follow the method LeSage and Pace (2009) suggested to test the significance of these coefficients by drawing parameter estimates 1000 times from the variance-covariance matrix of the parameter estimates to generate the distribution of these effects. The direct elasticities of capital per capita and intermediates per capita are 0.064 and 0.557, and both are strongly significant. The spillover effect of capital is negative and statistically insignificant, which indicates that the growth in capital of neighboring industries does not contribute to output growth of the industry itself. The main reason is that the increased usage of capital in the neighboring (supplier or customer) industries appear to have a negative effect on the industry itself because of the scarcity in capital. The adverse effects of this competitive relationship may counterbalance the spillover effects of complementary relationship among industries. The indirect elasticity of intermediate deepening is 0.262 and highly significant, indicating that industry's output growth could be benefited when its neighboring industries has increased the intermediate inputs. Therefore, when the spillover effect from intermediate input is incorporated, the output elasticity of intermediate input increases from 0.5567 to 0.8189, which can be attributed to intermediate augmenting-type technical progress because of the improvement of vertical specialization in the production network.

Table3: Direct, Indirect, and Total Elasticity of input factors

		Direct		Indirect		Total	
		Elasticity	asy. t-stat	Elasticity	asy. t-stat	Elasticity	asy. t-stat
overall	K/L	0.0640***	7.77	-0.0271	-0.80	0.0369	1.10
	M/L	0.5567***	68.01	0.2622***	9.38	0.8189***	28.81
domestic	K/L	0.0640***	7.77	-0.0196	-0.80	0.0445	1.81
	M/L	0.5566***	67.98	0.1893***	9.49	0.7458***	35.70
	K/L	0.0000	-0.79	-0.0075	-0.80	-0.0076	-0.80

international	M/L	0.0001***	6.19	0.0730***	8.76	0.0731***	8.75

Notes: Empirical standard deviations of the elasticity based on a 1000 MCMC draws using the variance-covariance matrix of the parameters following the algorithms of Lesage and Pace (2009, P.150). * Indicates significance at 5%; **Indicates significance at 1%; ***Indicates significance at 0.1%.

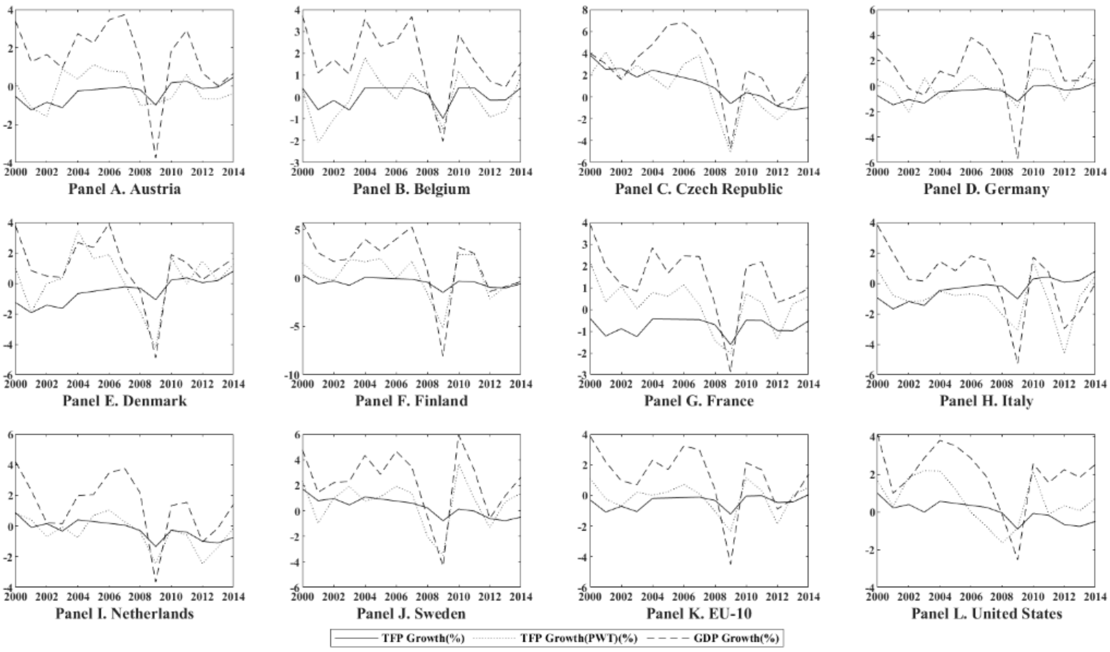
In order to distinguish the network effects that are based on domestic versus international industrial linkages, we followed Liu and Cheng (2021) and decompose the different spillover effects into domestic effects involving the domestic value chain and international effects involving the international value chain. As the last two rows of Table 3 show, the international indirect elasticity of intermediate input is 0.073 and is statistically significant, and accounts for approximately 28% of the overall indirect effects of the intermediate input. This suggests that 28% of the spillovers embodied in the intermediate input has transmitted across borders, which can be an important channel for production interactions among industries.

5. TFP Growth of EU

5.1 TFP Growth of EU economies

We also calculate the own industrial TFP growth g_t^{own} by Equation (5) in Section 2 and aggregate with Domar weights at the national level. Figure 2 shows the aggregate TFP growth of the 10 European countries and the US from 2000 to 2014. It is noticeable that TFP growth in all of the countries fell sharply in the global financial crisis, and rebounded in 2010, but fell again due to the Euro Area recession. The estimates are fairly close to the findings reported by the Penn World Table (Feenstra et al., 2015). As shown in Figure 2, the trend of TFP growth in these countries were basically consistent with their GDP growth during the 2000-2014 period, but presents a smaller fluctuation. We can see that the EU-10 (Panel K.) experienced a decrease in TFP growth from -0.29% in 2000 to -1.08% in 2001, gradually recovering to -0.11% in 2007. During the global financial crisis, the TFP growth rates had sharply fallen because of the slowing demand, weak investment and lingering structural rigidities (van Ark, 2016; van Ark and O' Mahony, 2016; Duval et al., 2020). Subsequently, TFP growth rebounded in 2010 and started to decline after the Euro Area recession. Compared with the TFP growth performance of the United States (Panel L.), before the global financial crisis of 2008, EU-10 TFP growth was lower than the average annual TFP growth of the United States (0.38%). Nevertheless, the decelerating trend of TFP growth in the US continued during the following years and TFP growth dropped to its lowest point in 2009 (-0.90%). Although TFP growth in the US rebounded in 2010, as did other economies in the EU-10, the rebound failed to return TFP to its pre-crisis growth rate, and then it declined again in 2011- 2014. This would seem to indicate that the global financial crisis may have induced a long term TFP growth slowdown, especially in US. One key reason for the slowdown of the technological progress in US is related to lower productivity enhancing investment (Bianchi et al., 2019; Anzoategui et al., 2019) in terms of R&D expenditure (% of GDP) and the number of patent applications.

Figure 2: Productivity Growth



We can see that annual TFP growth rates in all countries except the Czech Republic range between -2% and 1%. Over the sample period, Denmark, Italy, Germany, Austria, and Belgium showed an upward trend in annual TFP growth, from -1.27%, -0.98%, -0.75%, -0.55% and 0.41% in 2000 to 0.79%, 0.79%, 0.30%, 0.46% and 0.43% in 2014. In contrast, France, Finland, the Netherlands, Sweden, and the Czech Republic and showed a decline in TFP growth, from -0.41%, 0.33%, 0.87%, 1.71% and 3.84% in 2000 to -0.53%, -0.59%, -0.74%, -0.50% and -0.97% in 2014, respectively. Notably, the Czech Republic saw the fastest TFP growth before the global financial crisis, which can be attributed to its industrial structure and the benefits from GVC participation (van Ark et al., 2013). The Czech Republic is a small open economy with relatively large manufacturing sectors, and it is also the largest player in intra-regional trade in terms of manufacturing inputs among the

European economies.[9] Participating in GVCs has stimulated the TFP growth of manufacturing sectors in Czech Republic through specialization, knowledge spillovers, and learning by doing, among other factors (Criscuolo and Timmis, 2017).

5.2 TFP Growth by industry

In Table 4, we selected the top three industries with the fastest average TFP growth in each country during 2000 to 2014. One of the most prevalent industries in that list are those related to the digital economy. The Electrical Equipment industry in the United States, with the annualized average TFP growth of 4.80%, turned out to have the most rapid TFP growth of all industries in 2000-2014. Electrical Equipment industries of other countries also are high performing in terms of TFP growth, with 3.57% TFP annual growth in Sweden, followed by 2.37% in the Czech Republic, 1.61% in France, 1.42% in the Netherlands, and 1.39% in Germany. The Telecommunications industry also exhibited a high level of total average TFP growth in EU-10, and its average annual growth rates in Denmark, Finland, Italy, Sweden, the Netherlands, Germany, France, Belgium were 4.66%, 3.53%, 3.43%, 3.11%, 2.52%, 2.50%, 2.46% and 1.03%. The fast growth in these related industries benefitted from advances in information and communication technology (ICT) during this period (Oulton, 2012; Bloom et al., 2012). Rapid development of new products and production tools, such as robotics, artificial intelligence, and digital technologies penetrated the economies more and more extensively through the input-output network and the momentum of these new technology spillovers may impact TFP growth in other industries to a much greater extent in the future.

Table 4: Top three industries with the fastest TFP growth in EU-10 and US (%)

Country	Industry	TFP growth	rank	Country	Industry	TFP growth	rank
Austria	Coke, Refined Petroleum	3.61	3	Belgium	Mining, Quarrying	1.05	30
	Postal and Courier	1.68	17		Telecommunications	1.03	31
	Financial and Insurance Activities	0.88	35		Coke, Refined Petroleum	0.78	42
Czech Republic	Machinery, Equipment	2.97	8	Germany	Telecommunications	2.50	10
	Electrical Equipment	2.37	12		Electrical Equipment	1.39	26
	Transport Equipment	2.36	13		IT and other information services	1.03	32
Denmark	Telecommunications	4.66	2	Finland	Telecommunications	3.53	5
	Chemicals, Pharmaceuticals	1.64	19		Trade & Repair of Motor Vehicles	1.41	25
	Publishing, Media Services	1.61	21		Agriculture	1.07	29

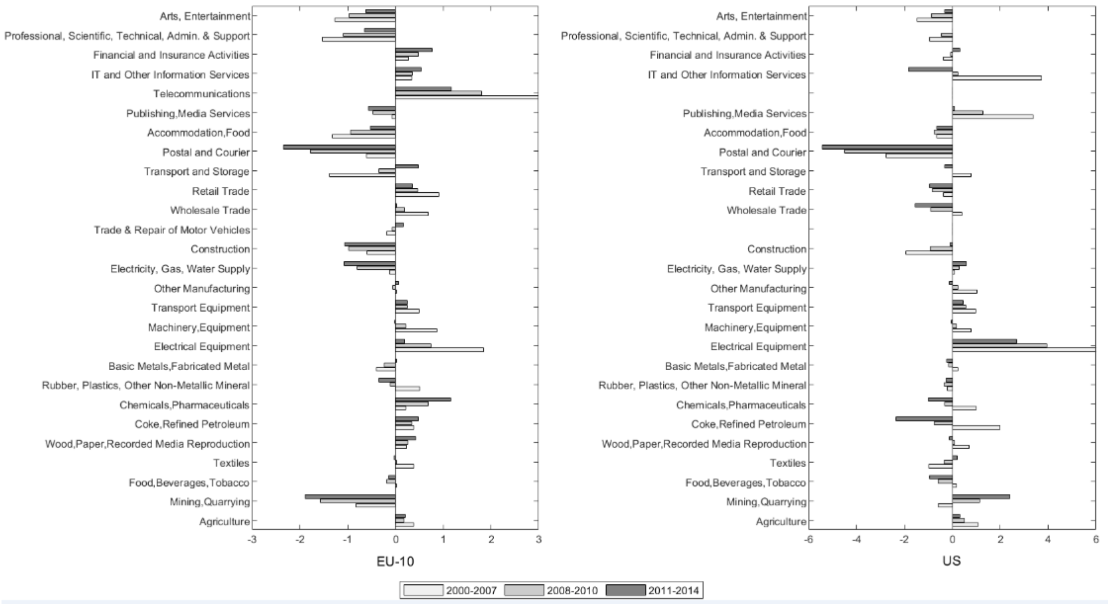
[9]Source: Organization for Economic Co-operation and Development Bilateral Trade in Goods by Industry and End-use database, International Standard Industrial Classification, Revision 4 (2016 edition).

France	Telecommunications	2.46	11	Italy	Telecommunications	3.43	6
	Electrical Equipment	1.61	20		Financial and Insurance Activities	1.09	28
	Agriculture	0.75	46		IT and other information services	0.54	66
Netherlands	Telecommunications	2.52	9	Sweden	Electrical Equipment	3.57	4
	Electrical Equipment	1.42	24		Telecommunications	3.11	7
	Financial and Insurance Activities	0.81	38		IT and other information services	1.71	16
United States	Electrical Equipment	4.80	1	EU-10	Telecommunications	0.02	0
	Publishing, Media Services	2.07	14		Electrical Equipment	0.01	0
	IT and other information services	1.52	22		Retail Trade	0.01	0

In Figure 3 we report the average annual industry TFP growth rate in the EU-10 and the US during three periods: 2000-2007, 2008-2010, and 2011-2014.[10] We can observe that the change of TFP growth showed less variations in the EU-10 average than the US. IT and Other Information Services, Coke & Refined Petroleum, Electrical Equipment, Publishing & Media Services had a 3% decline in average annual TFP growth rate for the US in 2010-2014 compared with 2000-2007. By contrast, the industry with the most significant decline of the EU-10 average TFP growth rate was Telecommunications (with 1.88% decline). The average annual growth rate falls from 3.05% in 2000-2007 to 1.17% in 2010-2014. Focusing on the EU-10 average, the slowdown of TFP growth after the global financial crisis appears to have been widespread and easily visible in several industries. Two exceptions to these trends are the Chemicals & Pharmaceuticals and Transport & Storage industries whose TFP growth after 2008 increased. When comparing the average industry TFP growth in the EU-10, Telecommunications and Electrical Equipment also had the fastest TFP growth over the full sample period from 2000 to 2014, as we discuss the industry-specific TFP growth above. Postal & Courier and Mining & Quarrying experienced a dramatic decrease in TFP, with the average annual growth from -0.61% and -0.82% declined to -2.35% and -1.88%, respectively.

Figure 3: Average of industry TFP growth

[10]According to the above results, the global financial crisis has significantly damaged the TFP growth of the European countries and the United States. Therefore, we divide the sample time period into three sub-periods: the pre-crisis period (2000-2007), the global financial crisis itself (2008-2010), and the post-crisis period (2011-2014).

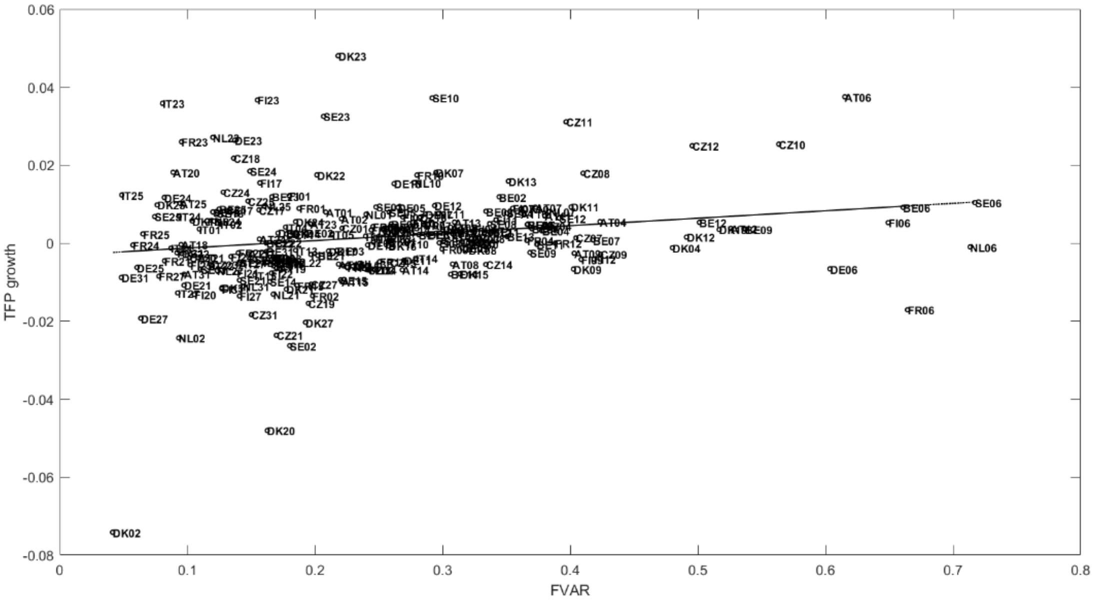


Notes：EU-10 refers to the average of the 10 countries TFP growth.

5.3 TFP Growth and Global Value Chain participation

In this section, we examine links between TFP growth and GVC participation in EU countries, which would help us to better understand how GVC participation could account for the change of industry TFP growth. GVC participation is represented by the foreign value-added ratio (FVAR) in our analysis, which reflects the ratio of foreign value added to gross exports and is calculated using the method developed by Wang et al. (2013). Figure 4 plots FVAR values against TFP growth rates for industries in 2007. To examine this correlation, we estimate the following regression model $g_{TFPi} = \gamma_0 + \gamma_1 FVAR_i + \varepsilon_i$. Here g_{TFPi} is the TFP growth rates of industry i; γ_0 is the intercept; $FVAR_i$ is the foreign value-added ratio; ε_i is an error term representing all other influences. OLS estimated parameter for $FVAR_i$ is 0.02 and significantly different from zero, which implies that there exists the positive relationship between industry TFP growth and FVAR for most industries in the EU-10. Increased involvement in the GVC, and the stronger production linkages with other countries this entails, may lead to a higher pace of TFP growth and may suggest that an industry generates faster TFP growth through technology spillovers of upstream and downstream industries in the global production network. FVAR is higher for Coke & Refined Petroleum (06) than other industries in Figure 4, mainly due to the energy import dependencies of European countries. Production of coke and petroleum products relies heavily on imported intermediate inputs.

Figure 4: FVAR and TFP growth for European industries in 2007



6. Spillover of TFP growth of EU Manufacturing sectors

The discussion above is focused on the TFP growth realized by the industry on its own. However, the rapid development of the global value chain boosted the spread of new knowledge and technology among the participating industries, especially those manufacturing industries interconnected in the production network. This means that technology progress exhibited by these industries are interdependent. The progress in an industry may provide spillovers to other industries through input-output linkages and these spillovers may propagate together to form the network effect. Our spatially specified model enables us to estimate the network effects in the global value chain setting. We will focus on the network effects between EU manufacturing sectors in this section.

6.1 Spillover of TFP growth by Economy

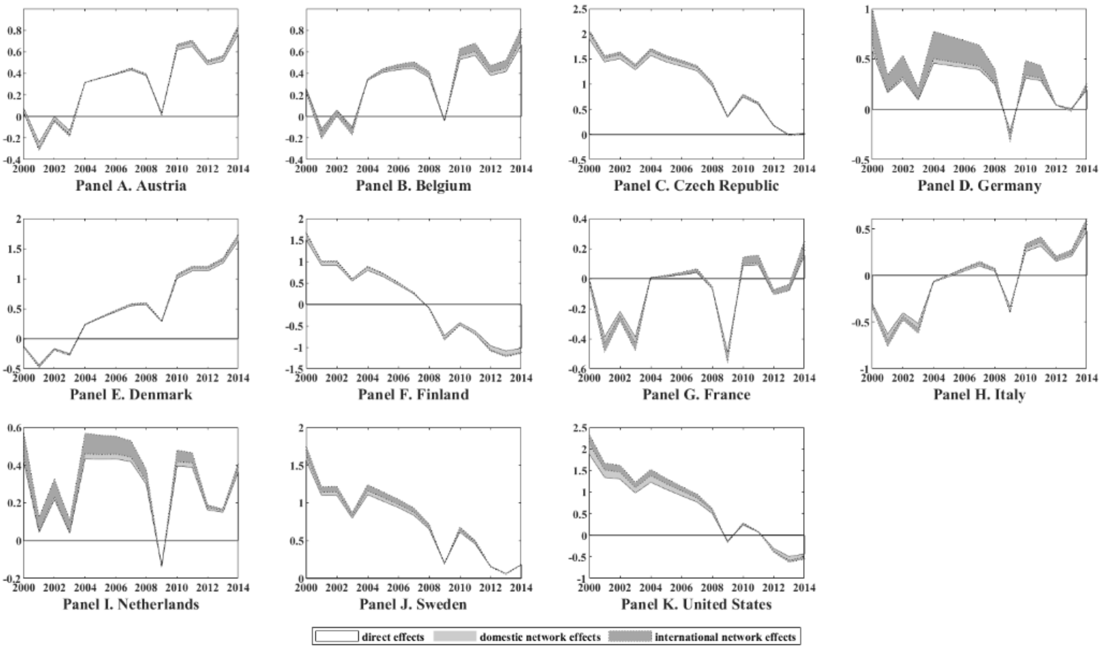
Figure 5 plots the aggregate own effect TFP growth superimposed with network effects offered by industries in eleven countries during 2000-2014.[11] In general, the own and network effects of TFP growth vary in the same directions. Germany offered the most, with 1.40‰ annual average domestic and 0.19‰ annual average international spillovers. The US offered the second highest, with 0.62‰ annual average domestic and 0.69‰ annual average international spillovers, followed by the Netherlands, the Czech Republic and Sweden. The other six countries provided a negligible annual average network effect.

[11]Figure A.1 in Appendix shows these effects from the receiving perspective. The results based on both perspectives are broadly similar, though the spillover measured by receiving is less than the spillover measured by offering.

From 2000 through 2014, the trend of total effects in Austria, Belgium, Denmark, France, and Italy, were similar and positive. Among these five countries, as a regional hub in the Euro area, Belgium contributed relatively more network effects through knowledge spillovers than the other four countries, especially after the global financial crisis. An explanation for this is deepening participation of Belgium manufacturing industries in global and local value chains (Dhyne and Duprez, 2017). It can be seen in Figure 5 that the Czech Republic, Finland, Sweden, Germany, and the Netherlands saw declines in the overall effects of manufacturing industry's TFP growth, but the decline was more prominent in the Czech Republic, Finland and Sweden. In contrast, Germany, as the most important hub in the intra-Europe production network and with strong linkages with other countries, declined relatively less than the other economies in TFP growth and provided the most positive international spillovers to the other economies by exporting high-technology and complex intermediate goods. Netherlands was the second largest contributor in TFP growth spillovers, mainly due to its well-developed manufacturing foundation and advanced port and logistics system. Recalling the GVC trade network in Figure 1, Netherlands provides a similar role as a transferring hub between the US and Germany, the two large advanced economies that set the productivity frontier in many industries.[12] In addition, the Czech Republic also provides relatively high growth spillovers along with its own rapidly increasing TFP. Comparing the domestic and international configuration of network effects, we can find that there were more international spillovers in European countries and more domestic spillovers in the US, which will be discussed in detail in the next section.

Figure 5: Direct and Network Effects of TFP Growth

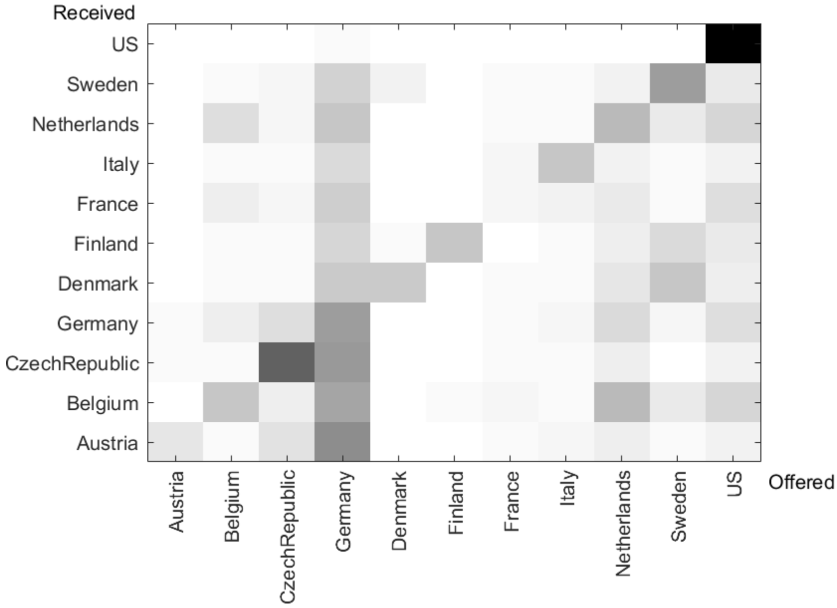
[12] https://www.worldbank.org/en/topic/trade/publication/global-value-chain-development-report-2019



6.2 Domestic and international spillovers

Figure 6 shows the distribution of network effects of TFP growth between each pair of offering-receiving countries in 2007. From the columns which represent the network spillovers offered by countries, Germany obviously offered the most to other industries in the entire production network (2.45‰), followed by the US (1.78‰), the Netherlands (1.10‰) and the Czech Republic (1.03‰), whereas other countries contributed only limited network effects. For almost all countries except Germany, the spillover effects in domestic production networks, which is represented in the diagonal blocks of the matrix in Figure 6, were higher than the corresponding spillover effects in the bilateral production networks with other countries. In the Czech Republic, Denmark and Finland the domestic network effects accounted for above 50% of the total network effects, indicating that the TFP growth spillovers were more likely to occur through domestic input–output linkages in these countries. In contrast, there were 50% - 86% spillover effects across borders in the United States, Austria, Italy, Sweden, Belgium, the Netherlands, France and Germany. Germany contributed the most technology spillovers to other countries, with international network effects of 2.11‰. Germany offered TFP growth spillovers of 0.39‰, 0.35‰, 0.31‰ to Austria, the Czech Republic and Belgium, respectively. The spillover the Czech Republic received from Germany is much more than other countries in our sample. This is not surprising since Germany is the biggest trading partner of the Czech Republic. Our estimates also suggest that the bilateral technology spillovers in Belgium *V.S.* the Netherlands, and Denmark *V.S.* Sweden, are relatively higher than other bilateral technology spillovers, which implies that their co-operation in value chains is more successful in promoting each other's TFP growth.

Figure 6: Distribution Matrix of Network Effects of TFP Growth among Countries



7. Conclusion

The increasingly close value chain cooperation in the European Union over the past several decades has become an important factor to boost the productivity growth for the countries who integrated into these production networks. The input-output linkages provide an important channel for the transmission of the technology and productivity spillovers among countries. In this paper, we develop a spatial production model that features technological interdependence and heterogeneous productivity growth at the industry level. We use our spatial model to measure TFP growth and spillover in the Europe. Our estimation results suggest that intermediate inputs have positive externalities for gross output and that about 27% of the spillover embodied in intermediate input has transmitted across borders. This can be an important channel for production interactions among industries. TFP growth in our sample countries fell sharply during the global financial crisis and the Euro Area recession. Germany offered the most network effects with 1.40‰ annual average domestic spillover and 0.19‰ annual average international spillover. The US offered the second highest amounts of network effects, followed by the Netherlands, the Czech Republic and Sweden. The other six countries, Austria, Belgium, Denmark, Finland, France, and Italy, provided a negligible annual average network effect. From a more detailed network perspective that distinguishes the source and destination of spillover effect by countries, we also find that Germany, as the most important hub in intra-Europe production networks, has the most international spillovers offered to its European counterparts over the entire sample.

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Appendix A

In this section, we obtain equation (3).

Taking the logarithm of Equation (2), we have:

$$\ln A_i\left(t\right)=\rho\sum_{j\neq i}^{N}w_{ij}\ln A_j\left(t\right)+\phi\sum_{j\neq i}^{N}w_{ij}\ln k_{jt}+\varphi\sum_{j\neq i}^{N}w_{ij}\ln m_{jt}+\ln\Omega_i(t) \qquad \text{(A1)}$$

We can rewrite equation (A1) as the following:

$$\left(1-\rho\sum_{j=1}^{N}w_{ij}\right)\ln A_i\left(t\right)=\phi\sum_{j\neq i}^{N}w_{ij}\ln k_{jt}+\varphi\sum_{j\neq i}^{N}w_{ij}\ln m_{jt}+\ln\Omega_i(t) \qquad \text{(A2)}$$

We can solve (A2) for $A_i\left(t\right)$, if $\rho\neq 0$ and if $1/\rho$ is not an eigenvalue of W:

$$\ln A_i\left(t\right)=\left(1-\rho\sum_{j=1}^{N}w_{ij}\right)^{-1}\left(\phi\sum_{j\neq i}^{N}w_{ij}\ln k_{jt}+\varphi\sum_{j\neq i}^{N}w_{ij}\ln m_{jt}+\ln\Omega_i\left(t\right)\right) \qquad \text{(A3)}$$

Replacing (A3) in the production function (1) written per worker, and then taking the logarithms, we have:

$$\ln y_{it}=\left(1-\rho\sum_{j=1}^{N}w_{ij}\right)^{-1}\left(\phi\sum_{j\neq i}^{N}w_{ij}\ln k_{jt}+\varphi\sum_{j\neq i}^{N}w_{ij}\ln m_{jt}+\ln\Omega_i\left(t\right)\right)+\alpha\ln k_{it}+\beta\ln m_{it} \qquad \text{(A4)}$$

Putting $\Omega_i(t)$ into (A4), rewrite function (A4) in matrix form as the following:

$$\ln\boldsymbol{y}=\rho\left(\boldsymbol{W}\otimes\boldsymbol{I}_T\right)\ln\boldsymbol{y}+\alpha\ln\boldsymbol{k}+\beta\ln\boldsymbol{m}+\Gamma_0+\Gamma_1 t+\Gamma_2 t^2+\boldsymbol{v}+(\phi-\alpha\rho)\left(\boldsymbol{W}\otimes\boldsymbol{I}_T\right)\ln\boldsymbol{k}+\left(\varphi-\beta\rho\right)\left(\boldsymbol{W}\otimes\boldsymbol{I}_T\right)\ln\boldsymbol{m}$$

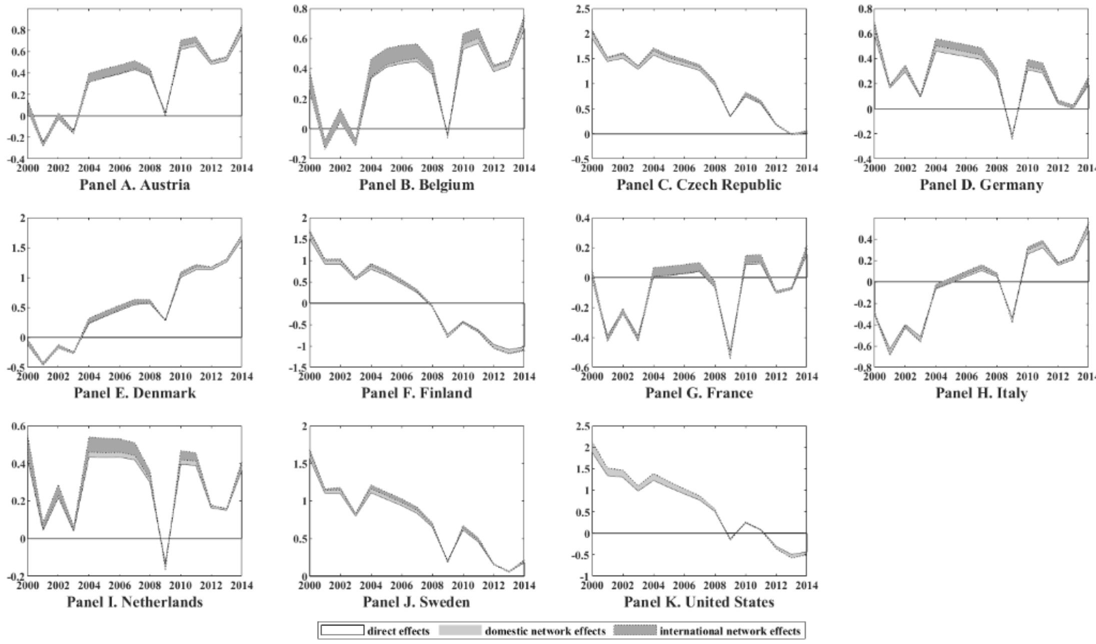
where $\boldsymbol{y}$, $\boldsymbol{k}$, $\boldsymbol{m}$ and $\boldsymbol{v}$ are $NT\times 1$ vectors, W is a $N\times N$ matrix, $\boldsymbol{\Gamma}_0=\ln\Omega_i(0)\otimes\boldsymbol{\iota}_T$, $\boldsymbol{\Gamma}_1=\delta_{1i}\otimes\boldsymbol{\iota}_T$, $\boldsymbol{\Gamma}_2=\delta_{2i}\otimes\boldsymbol{\iota}_T$, $\boldsymbol{\iota}_T$ is the T dimensional vector of ones.

Table A.1 Industry Classifications and Codes

No.	Industry	ISIC Rev. 4
1	Agriculture	A
2	Mining, Quarrying	B

3	Food, Beverages, Tobacco	10-12
4	Textiles	13-15
5	Wood, Paper, Recorded Media Reproduction	16-18
6	Coke, Refined Petroleum	19
7	Chemicals, Pharmaceuticals	20-21
8	Rubber, Plastics, Other Non-Metallic Mineral	22-23
9	Basic Metals, Fabricated Metal	24-25
10	Electrical Equipment	26-27
11	Machinery, Equipment	28
12	Transport Equipment	29-30
13	Other Manufacturing	31-33
14	Electricity, Gas, Water Supply	D-E
15	Construction	F
16	Trade & Repair of Motor Vehicles	45
17	Wholesale Trade	46
18	Retail Trade	47
19	Transport and Storage	49-52
20	Postal and Courier	53
21	Accommodation, Food	I
22	Publishing, Media Services	58-60
23	Telecommunications	61
24	IT and Other Information Services	62-63
25	Financial and Insurance Activities	K
27	Professional, Scientific, Technical, Admin. & Support Service	M-N
31	Arts, Entertainment	R-S

Chart A.1. Network Effects of TFP Growth among Different Countries


Panel A. Austria
Panel B. Belgium
Panel C. Czech Republic
Panel D. Germany
Panel E. Denmark
Panel F. Finland
Panel G. France
Panel H. Italy
Panel I. Netherlands
Panel J. Sweden
Panel K. United States
direct effects
domestic network effects
international network effects