Productivity Growth and Spillovers 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 the total factor productivity (TFP) growth and spillover for the 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.

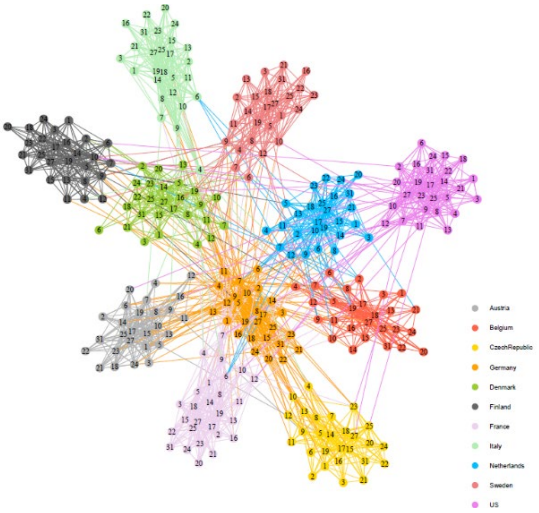
Figure 1 displays the inter-sectoral network across countries in the European area (as in Panel A and Panel C) based on the input-output linkages with a threshold of 2.5% for the percentage of the intermediate input in total intermediate purchased by each sector in the World Input-Output tables.[1] Panel 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.

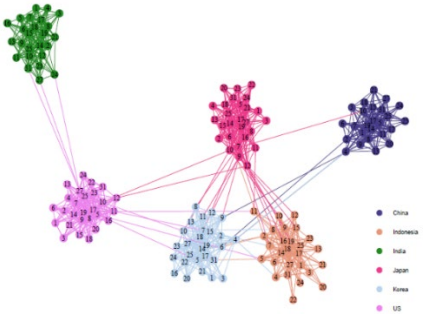
implies the changes in the pattern of supply chain across European countries. The total number of international linkages among the 297 industries of the ten European economies and the United States increased by one-third from 290 in 2000 to 384 in 2014, while the total number of domestic linkages declined 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.

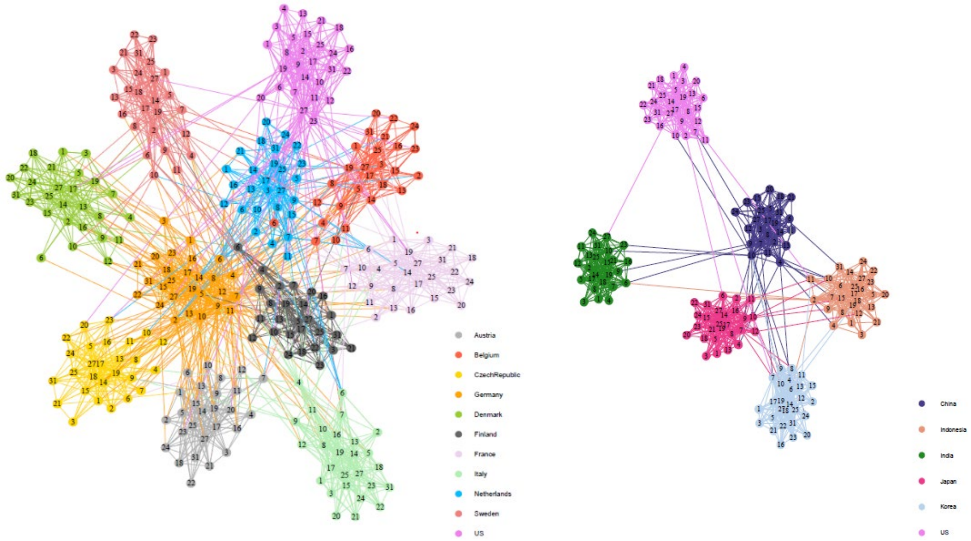
Figure 1: Intersectoral network corresponding to the World Input-output tables.

Panel A: Network of EU-10 and the US in 2000



Panel B: Network of Asia-Pacific and the US in 2000





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 examine the impact of technological spillovers on economic growth. However, the technology spillovers in this paper differ from the previous studies in terms of model specification. 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. This is because, as an important vector of knowledge diffusion, intermediate flows better represent

and reflect the 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) combine the methodology of spatial econometrics model and time-varying stochastic frontiers to estimate the industry-specific productivity and spillovers within the Asia-Pacific value chain. Following this method, Liu Sickles and Zhao (2022) estimate 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 linear technology progress and only measure the gross spillover received or offered by industry. Our current analysis considers the non-linear technology progress which is more consistent with the global trend in the slowdown of TFP growth and investigates the spillover from a more detailed network perspective that distinguishes the source and destination of spillover effect by countries in the Eurozone.

The main contribution of the paper is to investigate the TFP growth and spillover in European countries with a spatial stochastic frontier methodology. 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:

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

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. 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

$\Omega_i(t) = \Omega_i(0)\mathrm{e}^{R_i(t)+v_{it}}$, 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}

i 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 aggregate social capital, 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 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 as:

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

where y, k, m and v are $NT \times 1$ vectors, W is a $N \times N$ 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:

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

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

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

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 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 $R_i(t)' = \partial R_i(t) / \partial t = \delta_{1i} + 2\delta_{2i}t$, $\tilde{w}_{ij}$ 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:

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

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

[4]Although the latest EU KLEMS Growth and Productivity Accounts up to the 2019 release can be accessed, gross

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 and the price index derived from the latest published PWT version 9.1 (Feenstra et al., 2015). 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 in 2007, which is the mid-year of our sample period. The spatial weight matrix

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.

W

W is row

normalized, so that the 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 et al. (2016), Autor and Salomons (2018).

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 EU KLEMS. The real value data is based on tradition indicators i.e. capital stock and number of employees, which come from the WIOD database. 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. The coefficient of the spatially lagged dependent variable ρ is estimated between 0.2566 and 0.3286 and is statistically significant at 1% level, which suggest the positive network effects in production among the industries. Since the estimation results for the volume indices and real variables are consistent, our discussion is focused on the results of volume indices. As shown in the first two 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 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

	Index Variables				Real Variables			
	(1)		(2)		(3)		(4)	
parm	coef	std.err	coef	std.err	coef	std.err	coef	std.err
lnk	0.0655***	0.0084	0.0716***	0.0073	0.1510***	0.0119	0.1631***	0.0093
lnm	0.5543***	0.0081	0.5696***	0.0074	0.5747***	0.0080	0.6062***	0.0071
W•lnk	-0.0508*	0.0256	-0.0586***	0.0224	-0.1615***	0.0149	-0.1666***	0.0121
W•lnm	0.0472	0.0308	0.0011	0.0183	0.0649*	0.0308	-0.0105	0.0162
Year-dummy	yes		yes		yes		yes	
Intercept			-0.0272*	0.0111			-0.0060	0.0171
Time			0.0049**	0.0017			0.0017	0.0015
$Time^2$			-0.0002*	0.0001			-0.0001	0.0001
W•lny(ρ)	0.2566***	0.0335	0.2906***	0.0318	0.2886***	0.0324	0.3286***	0.0311
σ_v^2	0.0006		0.0006		0.0007		0.0007	
LL	9272		8881		9185		8808	
R^2	0.6890		0.6931		0.9090		0.9233	
Adjusted R^2	0.6100		0.6148		0.8859		0.9037	
	Time-varying FE		Time-varying RE		Time-varying FE		Time-varying RE	
Number of obs	3945		3945		3945		3945	

Notes: Time-varying FE denotes spatial CSS model (Cornwell, et al., 1990) with Fixed Effect and time-varying RE denotes spatial CSS model with Random Effects. "LL" denotes the loglikelihood. Significant at: *5, * *1 and * * * 0.1 percent.

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 0.065 and 0.556, 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 indirect elasticity of intermediate deepening is 0.252 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 0.5563 to 0.8082, 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	0.0650***	7.87	-0.0448	-1.36	0.0202	0.61
	M/L	0.5563***	69.95	0.2519***	9.62	0.8082***	29.91
domestic	K/L	0.0651***	7.87	-0.0326	-1.36	0.0325	1.34
	M/L	0.5562***	69.93	0.1831***	9.76	0.7392***	36.91
internationa l	K/L	0.0000	-1.32	-0.0123	-1.35	-0.0123	-1.35
	M/L	0.0001***	5.95	0.0688***	8.87	0.0689***	8.86

In order to distinguish the network effects between domestic and international industrial linkages, we decompose the spillover effects based on Equation (4b). As the last two rows of Table 3 show, the international indirect elasticity of intermediate input is 0.1831 and is statistically significant, and accounts for approximately 27% of the overall indirect effects of the intermediate input. This suggests that 27% of the spillovers embodied in the intermediate input has transmitted across borders, which can be an important channel for production interactions among industries.

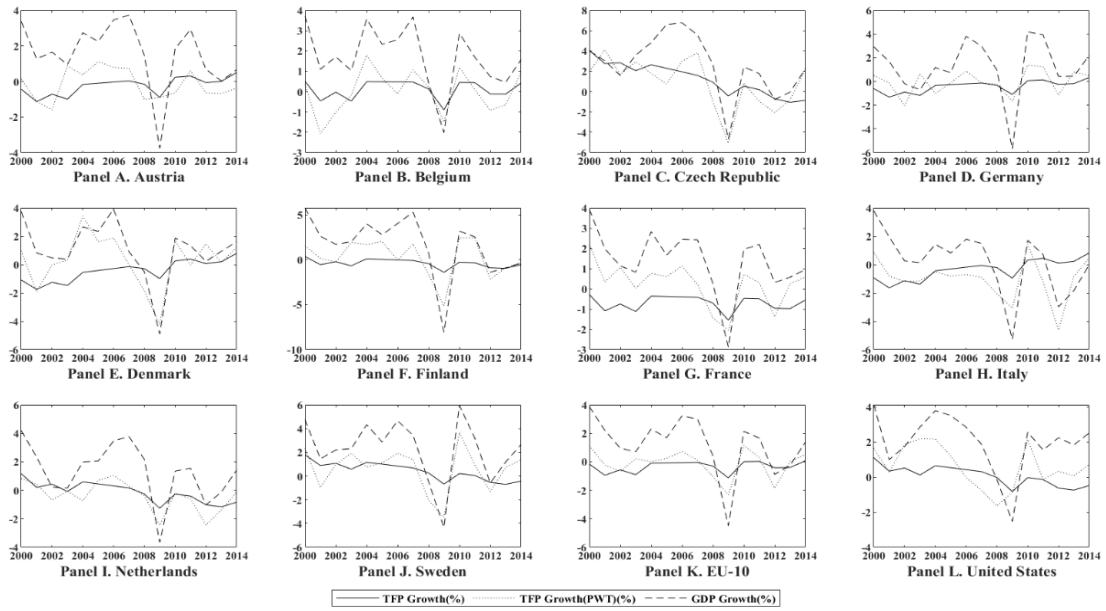
5. TFP Growth of EU

5.1 TFP Growth of EU economies

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 relatively modest fluctuation. We can see that the EU-10 (Panel K.) experienced a decrease in TFP growth from -0.16% in 2000 to -0.95% in 2001, gradually

recovering to -0.04% 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 (0.44%). 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 (-0.82%). 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 2%. Over the sample period, Italy, Denmark, Austria, and Germany showed an upward trend in annual TFP growth, from -0.94%, -1.09%, -0.44% and -0.61% in 2000 to 0.82%, 0.79%, 0.50% and 0.33% in 2014. In contrast, Sweden, Finland and the Netherlands show a sharp decline in TFP growth, from 1.79%,0.37%, and 1.16% in 2000 to -0.43%, -0.53% and -0.84% in 2014.

Meanwhile Belgium and France show a slight decrease in TFP growth, from 0.51% and -0.28% to 0.42% and -0.55%. 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.[7] 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 4.84%, 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 3.66% TFP annual growth in Sweden, followed by 2.41% in the Czech Republic, 1.65% in France, 1.53% in the Netherlands, and 1.43% in Germany. The Telecommunications industry also exhibited a high level of total average TFP growth in EU-10, and its average growth rates in Denmark, Finland, Italy, Sweden, the Netherlands, Germany, France, Belgium were 4.69%, 3.57%, 3.47%, 3.14%, 2.61%, 2.55%, 2.49% and 1.11%. 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	3.67	3	Belgium	Telecommunications	1.11	29
	Postal and Courier	1.70	18		Mining, Quarrying	1.05	33
	Financial and Insurance Activities	0.92	35		Financial and Insurance Activities	0.78	46

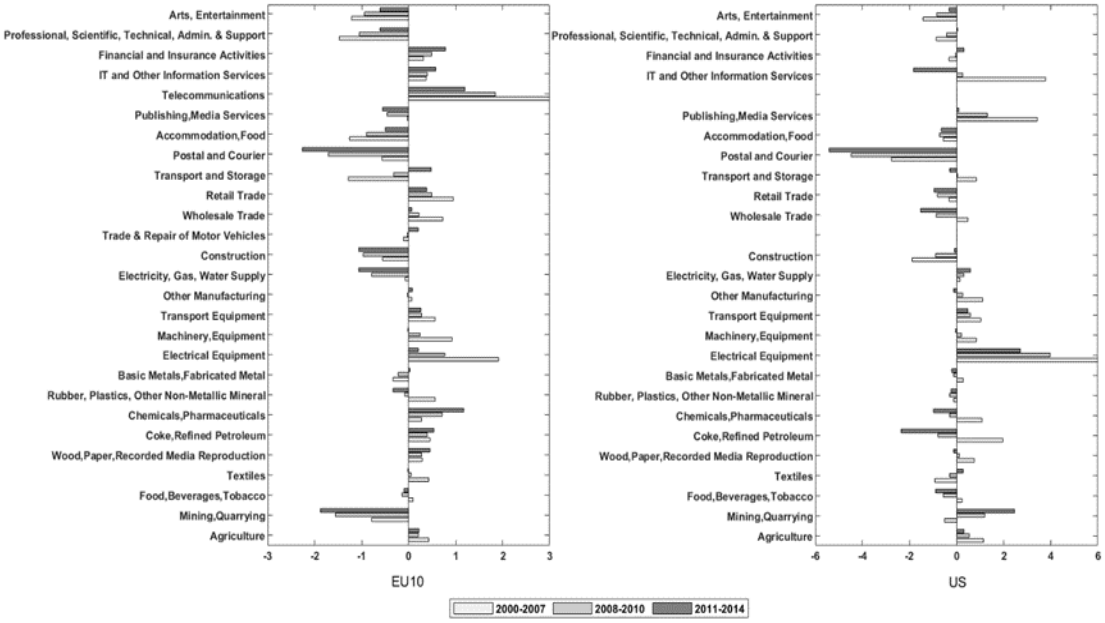
[7]Source: Organization for Economic Co-operation and Development Bilateral Trade in Goods by Industry and End-use database, International Standard Industrial Classification, Revision 4 (2016 edition).

Czech Republic	Machinery, Equipment	3.02	8	Germany	Telecommunications	2.55	10
	Transport Equipment	2.43	12		Electrical Equipment	1.43	25
	Electrical Equipment	2.41	13		IT and other information services	1.05	32
Denmark	Telecommunications	4.69	2	Finland	Telecommunications	3.57	5
	Chemicals, Pharmaceuticals	1.67	19		Trade & Repair of Motor Vehicles	1.42	26
	Publishing, Media Services	1.62	21		Agriculture	1.08	30
France	Telecommunications	2.49	11	Italy	Telecommunications	3.47	6
	Electrical Equipment	1.65	20		Financial and Insurance Activities	1.08	31
	Agriculture	0.79	45		IT and other information services	0.53	69
Netherlands	Telecommunications	2.61	9	Sweden	Electrical Equipment	3.66	4
	Electrical Equipment	1.53	23		Telecommunications	3.14	7
	Financial and Insurance Activities	0.78	47		IT and other information services	1.72	16
United States	Electrical Equipment	4.84	1	EU-10	Telecommunications	2.34	
	Publishing, Media Services	2.11	14		Electrical Equipment	1.23	
	IT and other information services	1.56	22		Retail Trade	0.70	

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.[8] 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 1.91% decline). The average annual growth rate falls from 3.12% in 2000-2007 to 1.20% 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 -0.56% and -0.79% declined to -2.27% and -1.88%, respectively.

[8]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).

Figure 3: Average of industry TFP growth

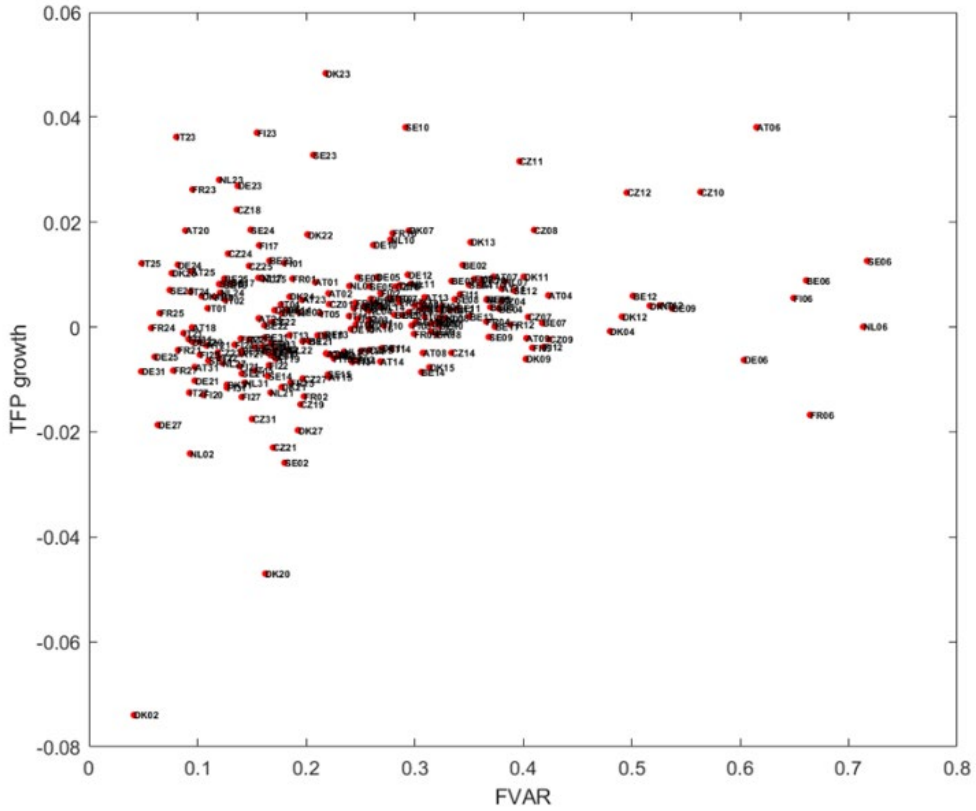


Notes：EU-10 refers to the average of the 10 countries TFP growth.

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. We note 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.

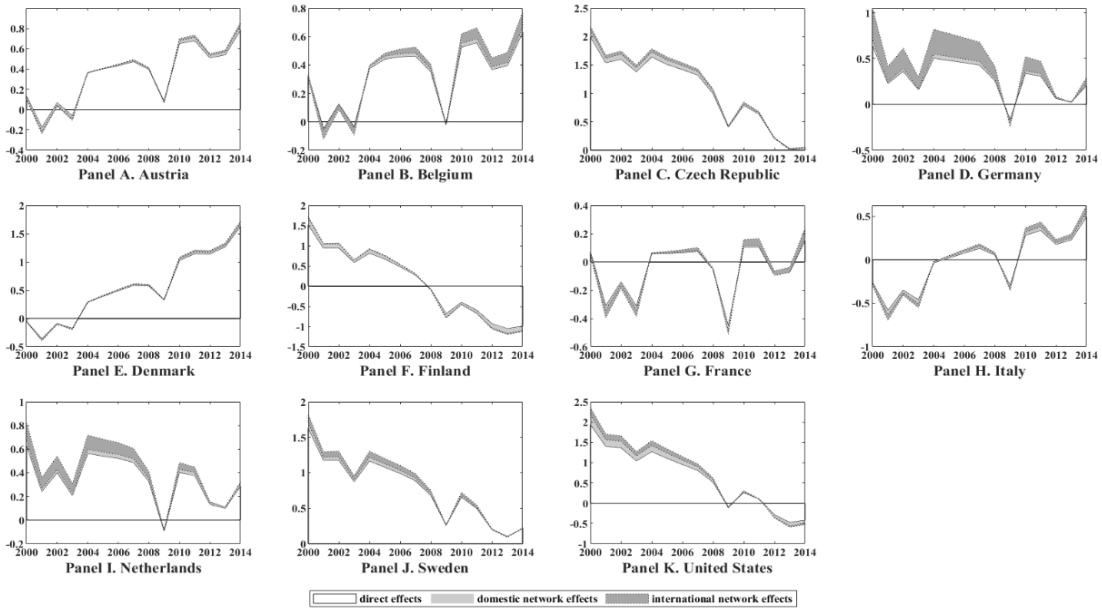
6.1 Spillover of TFP growth by Economy

Figure 5 plots the aggregate own effect TFP growth superimposed with network effects offered by industries in eleven countries during 2000-2014.[9] In general, the own and network effects of TFP growth vary in the same directions. From 2000 through 2014, the trend of total effects in Austria, Belgium, Denmark, France, and Italy, were similar and positive. Among these four countries, as a regional hub in the Euro area, Belgium contributed relatively more network effects through

[9]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.

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.[10] 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

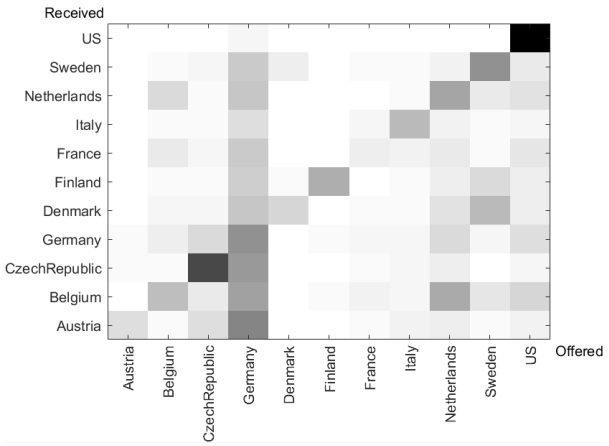


[10]https://www.worldbank.org/en/topic/trade/publication/global-value-chain-development-report-2019

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 (2.50‰), followed by the US (1.63‰), the Netherlands (1.19‰) and the Czech Republic (1.08‰), 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 Austria, the Czech Republic, Denmark, Finland, and the United States, 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 55% - 85% spillover effects across borders in Italy, Sweden, Belgium, the Netherlands, France and Germany. Germany contributed the most technology spillovers to other countries, with international network effects of 2.13‰. Germany offered TFP growth spillovers of 0.41‰, 0.34‰, 0.32‰ to Austria, the Czech Republic and Belgium, respectively. 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 between 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. Moreover, industries related to the digital economy have experienced the fastest TFP growth in most countries during the sample period, with Telecommunications having the highest TFP growth followed by Electrical Equipment. 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:

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

We can rewrite equation (A1) as the following:

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

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

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

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

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

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

$$\ln \boldsymbol{y} = \rho (\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{y} + \alpha \ln \boldsymbol{k} + \beta \ln \boldsymbol{m} + \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_1 t + \boldsymbol{\Gamma}_2 t^2 + \boldsymbol{v} + (\phi - \alpha\rho)(\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{k} + (\varphi - \beta\rho)(\boldsymbol{W} \otimes \boldsymbol{I}_T) \ln \boldsymbol{m}$$

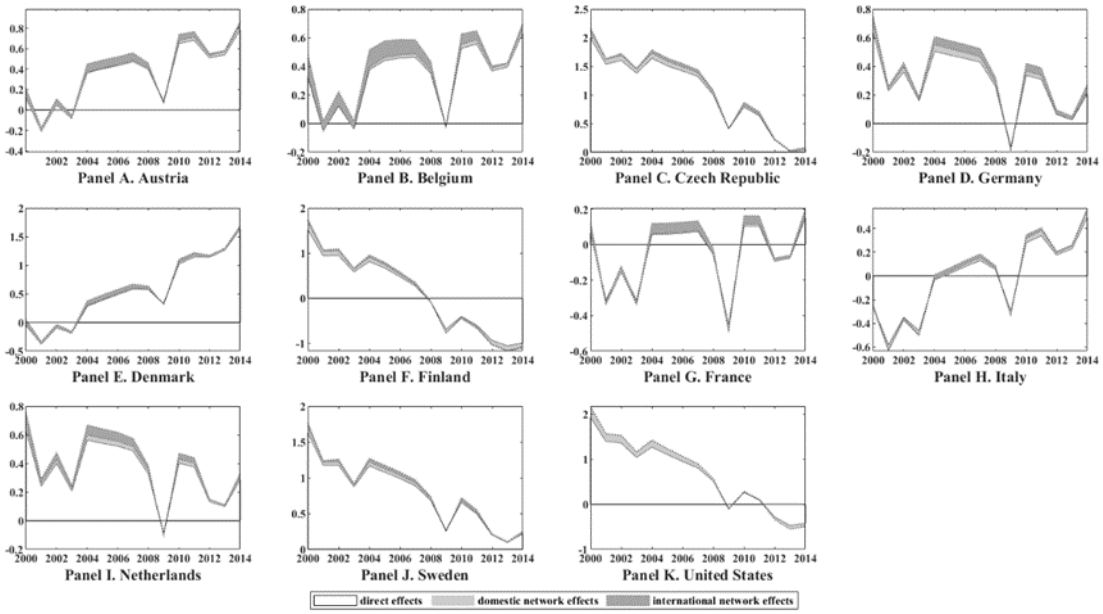
where $\boldsymbol{y}$, $\boldsymbol{k}$, $\boldsymbol{m}$ and $\boldsymbol{v}$ are $NT \times 1$ vectors, W is a $N \times N$ matrix, $\boldsymbol{\Gamma}_0 = \ln \Omega_i(0) \otimes \boldsymbol{\iota}_T$,

$\boldsymbol{\Gamma}_1 = \delta_{1i} \otimes \boldsymbol{\iota}_T$, $\boldsymbol{\Gamma}_2 = \delta_{2i} \otimes \boldsymbol{\iota}_T$, $\boldsymbol{\iota}_T$ 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 between 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