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Beyond Borders: How Spillovers and Commercial Networks Shape European Productivity

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Abstract

Understanding the drivers of economy-wide productivity growth has long been of interest to academics and policy makers. In this paper, we contribute to the literature by conducting a comprehensive analysis of the impact of technical change and catch-up on economic development in European regions. In doing so, we differentiate the internal productivity growth of each sector from the external spillover effect across both regions and sectors. As our study is much more granular than previous studies, we provide fundamental information for regional and national agencies to design effective policy measures aiming to stimulate regions' economic growth. We model the spatial interdependencies among the European regions using inter-regional and inter-sectoral input-output tables from the EUREGIO database. Our empirical application shows that the trade-related spillover effects cannot be disregarded, and that neglecting them would hide part of the explanation behind changes in productivity across regions. We conduct various counterfactual analyses to demonstrate this augmented impact of the trade network. We also simulate the regional TFP improvements due to digitalization, as well as the propagation effects of the financial crisis and the downturn in the construction sector. These analyses reveal how more traditional approaches that overlook these indirect effects tend to underestimate the true impact of positive and negative shocks on regional productivity growth. Our findings could serve policymakers as the ground for building a categorization of regions based on their presence in trade networks.

JEL codes: C23, F43, O47.

Keywords: Spatial econometrics, total factor productivity, trade networks, spillovers, regional European economic growth.

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1. Introduction

Understanding the drivers of economy-wide productivity growth has long been of interest to academics and policy makers, given that differences in aggregate productivity are a key source of large cross-regional income differentials. Country and region-level studies typically focus on aggregate productivity and concentrate on two main sources of productivity growth: the shift in the relative size of industries and changes in industry productivities.¹ Many studies focus on sector-specific productivity changes and its components. Much of the literature on decomposing such productivity growth concentrates on two of its sources. One is due to the slow adoption by some production units of more productive technologies (i.e. they exhibit low levels of innovation). The other is that these units do not operate technologies efficiently due to diffusion and learning limitations. In the literature using frontier techniques, these two productivity growth drivers are labeled as technical change (shifts in the technology frontier) and catching-up (efficiency change).²

The analysis of the abovementioned productivity drivers on economic growth has predominantly focused on the country level, with only a limited number of studies exploring this topic at regional and sectoral levels. A quite recent exception is [Capello and Cerisola \(2023\)](#) who find that the deindustrialization of European regions was accompanied by a decline in productivity growth. Another study, by [Beugelsdijk et al. \(2018\)](#), finds large and persistent differences in economic development across subnational regions in European Union countries, which can largely be attributed to differences in total factor productivity (TFP). Their analysis shows that 75% of the difference in regional economic development can be explained by differences in TFP across regions. Several researchers (see e.g. [Brock and Durlauf, 2001](#), and [Gómez-Loscos et al. 2020](#)) point out that country-level analyses may both hide very different regional economic developments and bias the results in modeling economic growth across countries. Therefore, studying the regional dimension of TFP is important to uncover the heterogeneity often overlooked in country-level analyses. We should also consider the sectoral structure as an important driver of regional productivity disparities. For instance, [Acemoglu et al. \(2014\)](#) found that deindustrialization is one of the causes for the regional productivity disparities observed in the US because the manufacturing sectors exhibit higher productivity growth compared to the services sectors.

As productivity growth is one of the most important drivers behind regional income growth, interest in the analysis of productivity at the regional level has grown considerably in recent years. In this paper, we contribute to this still emergent literature by conducting a comprehensive analysis of the impact of technical change and catch-up on economic development in European regions. In doing so, we differentiate the internal productivity growth of each sector from the external spillover effect across both regions and sectors. The literature on the role of the trade network and spatial spillovers in explaining the differences in regional TFP in Europe is quite sparse because, until very recently, there was not a detailed subnational trade database ([EUREGIO; Thissen et al. 2018](#)) that made it possible to identify and estimate both types of spillovers. As far as we are aware, ours is the first attempt to consider inter-regional links and the position of regions within the commercial network when measuring regional and sectoral TFP growth in Europe. Our empirical application shows that the trade-related spillover effects are far from negligible, and hence they are not only essential for understanding regional economic performance and their vulnerability to internal and external shocks but also serve to design effective place-based development policies, regional innovation strategies, or smart specialization initiatives ([Barca, 2009; Thissen et al., 2013; McCann and Ortega-Argilés, 2016](#)).

¹ [De Avillez \(2012\)](#) called the first source the *reallocation effect*, and the second source the *within effect*. A survey of the literature on aggregate productivity can be found in [Balk \(2016a, b\)](#) and [Sickles and Zelenyuk \(2019\)](#).

² [Orea \(2002\)](#) and [Färe, Grosskopf, Norris, and Zhang \(1994\)](#) included a scale efficiency component into the decomposition using econometric and nonparametric frontier techniques respectively.

Our paper is thus related to the literature analyzing inter-regional and inter-sectoral spillover effects. Regarding the first type of spillover effects, [Alvarez et al. \(2016\)](#) conclude that the relative magnitude of the spatial spillover effects increases with the level of territorial disaggregation, i.e. they are more important at the provincial or regional level, compared to the national scale. Their findings are also in line with several other previous studies (see e.g. [Cantos et al., 2005](#); and [Rodríguez-Pose et al., 2012](#)) emphasizing that the existence of spatial spillovers in public capital, mainly in infrastructures, predominate at the regional level. It is worth mentioning in this sense that traditional TFP growth decompositions often ignore the existence of spatial spillovers. To address this issue, [Glass et al. \(2014\)](#) extend the standard TFP growth decomposition to include both direct (own) and indirect (spillover) components using a spatial autoregressive production frontier model.³

As previously mentioned, a distinctive feature of the empirical strategy used in our paper is that it also allows the measurement of inter-sectoral spillovers among the European regions.⁴ Regions differ considerably from countries in terms of inter-sectoral linkages. They are more open to trade, which exposes them to important external dependencies ([Isard, 1951](#)). Moreover, they also differ substantially among each other in their specialization patterns, leading to differences in their position within the commercial networks ([Fingleton et al., 2012](#)). With the progression of globalization and the lowering of trade barriers over the last decades, we have witnessed the process of spatial fragmentation, and offshoring of production ([Baldwin and Venables, 2013](#)). For regions, this has translated into their external dependencies becoming global, making their economies more exposed to downturns and supply chain disruptions occurring in other parts of the world ([Tranos et al., 2023](#)). As a result, regions have had significantly different experiences in terms of both suffering and recovering from negative economic shocks, as highlighted by [Kitsos et al. \(2023\)](#). Moreover, the sectoral composition could play a significant role in the transmission of shocks between countries or regions ([Gadea-Rivas et al., 2019](#)).

The inter-regional approach we adopt in this paper is advocated because there is growing evidence that trade and technological spillovers across regions (countries) are major drivers of economic growth. Economic growth in Europe is not an exception as the economies of the European countries have a high level of interdependence ([Sun et al. 2013](#)). This feature is exhibited in [Figure 1](#), which provides a visual representation of the network of regional trade flows for nine European countries in the years 2000 and 2010. This figure shows how the network is considerably dense, showcasing the large amount of trade interactions happening at the regional level between European economies. The figure clearly reveals distinct patterns in the position and the number of connections between regions. In both years, some German, French and Italian regions occupy central positions within the network, albeit some of the regions from these countries also appear on the periphery. This clearly supports our aforementioned comments, indicating that specialization and openness to trade differs by region.

[Insert Figure 1 here]

Our empirical growth model is inspired by [Liu et al. \(2022a, b\)](#), [Liu and Sickles \(2023\)](#), and [Han and Sickles \(2024\)](#) who develop an empirical growth model that combines spatial spillovers and productivity growth heterogeneity at the industry-level. They use global value chain (GVC) linkages from inter-country input-output tables to model the technological interdependence between industries, and reveal

³ [Orea and Álvarez \(2019\)](#) point out that, although there is an extensive spatial econometric literature dealing with spatial interactions across units, the literature on spatial dependence in production frontier models has not generally taken spatial effects into account. Several studies have found that failure to account for spatial correlation effects in SF models results in biased estimates of efficiency scores. For this reason, it is important to use an econometric framework that allows one to control for the presence of cross-sectional dependence when measuring the efficiency performance of spatially distributed production units. A summary of this recent literature can be found in [Ayouba \(2023\)](#).

⁴ A relevant contribution to this research topic using production functions can be found in [Baltagi et al. \(2016\)](#). In addition to capturing spatial correlations in the model using a modified Hausman-Taylor approach, their paper accounts for inter-sectoral spillovers that affect firms' productivity in China's chemical industry.

a non-negligible network effect of TFP growth from one country to another through input-output linkages.⁵ The main feature of the production model introduced by these authors is its flexibility, as the proposed specification is sufficiently flexible to capture geographical and sectoral heterogeneity. While these authors use country-level data, our paper is the first attempt to estimate the proposed production model for a large set of (European) regions that are highly linked via the commercial network. Moreover, previous studies are much less granular, and thus conclusions cannot be drawn about any regional spillovers, something essential in order to allow regional and national agencies at all levels the possibility of designing effective and empirically-based policies using insights from research on the subject.

In our analysis, we estimate a neoclassical output per worker growth model, augmented by [Ertur and Koch \(2007\)](#) to include spatial externalities in knowledge. Instead of relying on geographical distance to construct the spatial weights matrix, we model the spatial interdependencies between European regions using inter-regional and inter-sectoral input-output tables from the EUREGIO database. We also follow [Glass et al. \(2016\)](#), who estimate these effects based on spatial production functions but calculate the industry-specific productivity growth spillovers by distinguishing between knowledge receiving and offering, which represent the two distinct directions of knowledge diffusion. Finally, by comparing sectors, we identify which ones can (or cannot) produce more output with the same amounts of inputs, and compute inefficiency scores for each industry. Furthermore, unlike [Glass et al. \(2016\)](#) who imposed distribution assumptions, we combine spatial econometrics with the previous work of [Cornwell et al. \(1990\)](#) (henceforth CSS) for estimation, which does not require further parametric assumptions on the distribution of the inefficiency term.

The model and its estimates allow us to test the existence of both inter-regional and inter-sectoral spillovers that shape the European regions' total factor productivity. In a spatial production model, we can also examine how regions' value added depends on the input changes of neighboring regions and upstream/downstream sectors via the input-output linkages across sectors and regions. Moreover, using the estimated parameters, we perform several simulations (symmetric and asymmetric shocks) to visualize better how spillovers and commercial networks shape European productivity. We conduct various counterfactual analyses to explore the productivity effects of several interesting factors, such as changes in trade size (i.e. in the degree of embeddedness of each sector-region pair); changes in trade network (i.e. in the share of each sector-region pair in total trade); and TFP improvements due to digitalization. We also simulate the global effects of two sector-specific productivity shocks: the negative productivity shocks due to the financial crisis in the Construction sector, and in the Real Estate, Financial and Business services sector.

The structure of the paper is as follows. In [Section 2](#), we introduce the econometric approach, and outline the methodology used to estimate the direct (own) and indirect (spillover) components of TFP growth. [Section 3](#) describes the data sources utilized in our analysis. In [Section 4](#), we present both the parameter estimates, the computed inter-regional and inter-sectoral spillovers between the European regions, and the main results of the performed simulations. Finally, [Section 5](#) presents the conclusions.

2. Empirical specification and estimation strategy

In this section, we first present our inter-regional (spatial) and inter-sectoral production model that allows for heterogeneous technological progress and technology spillovers. We next outline the estimation

⁵ Recent papers using inter-regional or inter-sectoral approaches include [Acemoglu et al. \(2016\)](#), who test the propagation mechanisms of TFP shocks through the input-output network at the industry level; [Carvalho and Tahbaz-Salehi \(2019\)](#), who present the theoretical foundations for the role of input-output linkages as a channel for shock propagations; and [Timmer and Ye \(2018\)](#), who summarize the effect that the global value chain has on the productivity of industries through these input-output linkages. [Bonadio et al. \(2021\)](#) also examine the role of global supply chains in the impact of the Covid-19 pandemic on GDP growth to simulate a global lockdown as a contraction in labor supply.

strategy used to estimate our model. We finally examine the spillover effects of factor inputs and TFP growth.

2.1. A Production Function with Heterogeneity and Spillovers

Let us assume that the technology of unit i at time t is characterized by a Cobb–Douglas production function with constant returns to scale in per worker terms:

$$y_{it} = A_{it}k_{it}^\alpha, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (1)$$

where $y_{it} = Y_{it}/L_{it}$ is value added per worker, $k_{it} = K_{it}/L_{it}$ is capital services per worker, and A_{it} is the aggregate level of productivity, which differs among production units and time periods.

We relax the assumption of identical Hicks-neutral technical change in the Solow model (Solow, 1956; Swan, 1956; and Ertur and Koch, 2007) by allowing each unit i to have its own specific technical progress while at the same time relaxing the assumption of cross-sectional independence by allowing the unit to absorb knowledge diffusion from its neighbors. The production unit we specify and analyze empirically in our study is a sector-region pair and hereafter use the spatial terminology, referring to region-sector pairs whose output are cross-sectional correlated through the commercial network as neighbors.

We start by allowing knowledge diffusion to be influenced by the strength of inter-regional and inter-sectoral linkages between neighboring region-sector pairs. Indeed, productivity growth originating in supplier industries may bring higher quality intermediates and know-how to downstream industries. Similarly, productivity growth occurring in customer industries may increase the requirement of intermediate quality and thus stimulate learning and capability building to upstream industries. Given the relevance of the input-output linkages in the diffusion of knowledge and R&D, we allow A_{it} to depend on the neighboring region-sector pairs' labor productivity, i.e., y_{jt} for all $j \neq i$. The Solow residual thus is expressed as:

$$A_{it} = e^{R_t' \delta_i} \prod_{j \neq i}^N y_{jt}^{\rho w_{ij}}, \quad (2)$$

where the weight w_{ij} formalizes the connectivity thought the input-output between region-sector pair i and region-sector pair j , R_t is an $L \times 1$ component that affects each sector (in our empirical model we utilize a constant and a time trend so that $L=2$), δ_i is an $L \times 1$ vector of coefficients that depends on i .⁶ Contained in the constant is the sector-specific initial technology state. With this specification we can identify input-output links that drive knowledge spillovers if ρ is positive. The per worker production function thus becomes:

$$y_{it} = e^{R_t' \delta_i} \prod_{j \neq i}^N y_{jt}^{\rho w_{ij}} k_{it}^\alpha. \quad (3)$$

The coefficient δ_i is expressed in terms of deviations (u_i) from its mean δ_g and we interpret $R_t' \delta_g$ as a global constant and technology growth term and $R_t' u_i$ as a unit-specific initial technology state and technology growth term. We use a time trend as the standard proxy for technological growth. Taking logarithms of the expression, we obtain the following production model:

$$\ln y_{it} = \rho \sum_{j=1}^N w_{ij} \ln y_{jt} + \alpha \ln k_{it} + R_t' \delta_g + R_t' u_i + v_{it}, \quad (4)$$

where v_{it} is the usual *iid* zero mean disturbance term with variance σ_v^2 . The u_i are specified as *iid* zero mean random variables with covariance matrix Δ . If u_i is constant and $\rho = 0$, then equation (4) reduces to the standard panel data model with a time trend. Notice that equation (4) is an example of a *spatial*

⁶ The estimator could be set up to include more variables in R_t such as proxies for innovation, proximity to the coastline, etc. We follow Diewert and Wales (1992) and Wooldridge (2015) to describe the technology by an exogenous time trend. However, we use a more flexible specificity by allowing the coefficients of constant and time trend (δ_i vector) to be region-sector specific. Therefore, δ_i already considers the regional characteristics that may influence productivity and productivity growth.

autoregressive (SAR) model where the spatial lag of the dependent variable (or the weighted average of neighboring values of the dependent variable) is included as an additional output driver.

The production function in equation (4) specifies a time-invariant elasticity of capital services. However, the global average capital share shows a continuous increase over past decades (Piketty, 2014; Autor et al., 2017; ILO, 2019). To accommodate this empirical finding we modify the Hicks-neutrality of productivity change in the underlying non-spatial model by allowing capital deepening to change over time.⁷ This modification is also made in our spatial generalizations. Our SAR model thus becomes:

$$\ln y_{it} = \rho \sum_{j=1}^N w_{ij} \ln y_{jt} + \alpha \ln k_{it} + \beta \ln k_{it} t + R_t' \delta_g + R_t' u_i + v_{it}. \quad (5)$$

We can express equation (5) more compactly as:

$$\ln y = \rho(W_N \otimes I_T) \ln y + \alpha \ln k + \beta \ln k \cdot t + r \delta_g + QU + V, \quad (6)$$

where y , k , m and V are $NT \times 1$ vectors, W_N is a $N \times N$ matrix with diagonal elements set to 0, ι_N is N dimensional vector of ones, $R = (R_1, R_2, \dots, R_T)'$, $r = \iota_N \otimes R$, $Q = \text{diag}(\iota_N) \otimes R$ is $NT \times LN$ matrix, δ_g is $L \times 1$ vector, and U is a $LN \times 1$ vector.⁸

Productivity spillovers are allowed to not only be influenced by other region-sectors' labor productivity, but also by other sectors' technology (A_{jt}) and capital-labor ratio (k_{jt}). The factor allocation in upstream or downstream industries may influence the allocation efficiency of the industry in question through its production network, which is in accordance with the network drivers discussed by Acemoglu et al. (2012) and Baqaee and Farhi (2020). This leads to the following expression for (the log of) technology:

$$\ln A_{it} = \rho \sum_{j=1}^N w_{ij} \ln A_{jt} + \phi \sum_{j=1}^N w_{ij} \ln k_{jt} + \delta_g R_t' + R_t' u_i + v_{it}. \quad (7)$$

Solving for $\ln A_{it}$ and rewriting in matrix form we have:

$$\ln A = \Omega(\phi(W_N \otimes I_T) \ln k + \delta_g r + QU + V). \quad (8)$$

where $\Omega = (I - \rho W_N \otimes I_T)^{-1}$ is the so-called global multiplier. Replacing this expression in the production function and multiplying both sides of the equation by $(I - \rho W_N \otimes I_T)$, we extend equation (4) and obtain the production function with (non-spatial) Hicks neutral technological progress in a Spatial Durbin form:

$$\ln y = \rho(W_N \otimes I_T) \ln y + \alpha \ln k + (\phi - \alpha \rho)(W_N \otimes I_T) \ln k + \delta_g r + QU + V. \quad (9)$$

A similar expression can easily be derived for the Spatial Durbin form of the spatial production function specified in equation (5)⁹:

⁷ The Hicks neutral vs. non-neutral terminology is only used for the underlying non-spatial model. Even if the underlying non-spatial model may specify productivity growth as Hicks-neutral, the proposed spatial models do not display Hicks-neutrality. Therefore, the spatial specifications allow for a much richer characterization of productivity growth in the production network than a simple non-spatial model.

⁸ Recall from equation (3) that the coefficient δ_i is expressed in terms of deviations (u_i) from its mean δ_g . In the stochastic frontier paradigm, while changes in $R_t' \delta_g$ can be viewed as technical change (hereafter TC), $u_{it} = R_t' u_i$ can be interpreted as capturing the technical (in)efficiency of unit i at time t . Cornwell et al. (1990) showed that we can use the estimated time-varying individual effects (here \hat{u}_{it}) to get time-varying efficiency scores for each region-sector pair. For each region-sector at year t we can define the maximum and calculate region-sector pairs' inefficiency relative to the 'best' region-sector pair in that year. That is, once $\hat{u}_{it} = R_t' \hat{u}_i$ is estimated, the following transformation is used for each region-sector pair $i \in s$ to get its inefficiency level: $EF_{it} = \exp(\hat{u}_{it} - \hat{u}_t^s)$, where $\hat{u}_t^s = \max_{i \in s}(\hat{u}_{it})$ varies over time. Note that the above transformation allows expressing $R_t' \delta_i$ as the sum of region-sector inefficiency (i.e. $\hat{u}_{it} - \hat{u}_t^s$) and a composed technological component (i.e. $R_t' \delta_g + \hat{u}_t^s$). That is, in a CSS setting, we should add the sector-specific technical change term ($\partial \hat{u}_t^s / \partial t$) to the global technical change term ($\partial R_t' \delta_g / \partial t$).

⁹ The function of technology in Spatial Durbin form is:

$$\ln A = \Omega(\phi(W_N \otimes I_T) \ln k + \phi(W_N \otimes I_T) \ln k \cdot t + \delta_g r + QU + V).$$

$$\ln y = \rho(W_N \otimes I_T) \ln y + \alpha \ln k + \beta \ln k \cdot t + (\phi - \alpha\rho)(W_N \otimes I_T) \ln k + (\varphi - \beta\rho)(W_N \otimes I_T) \ln k \cdot t + \delta_g r + QU + V. \quad (10)$$

2.2 Estimation

While one can apply standard fixed effects (FE) panel data estimation methods to estimate a non-spatial model that ignores inter-regional and inter-sectoral spillovers,¹⁰ either a SAR or SDM are the specifications of the production model that require nonlinear methods, relying on variants of quasi-maximum likelihood estimation (QMLE) procedure. These have been discussed widely in the literature for average production functions. For the stochastic frontier paradigm these methods require some modifications and are detailed in [Glass et al. \(2016\)](#). QMLE enables us to minimize the number of parameters to be estimated via the concentrated likelihood function instead of using the full likelihood function. We can find closed-form solutions for the parameters, except for the spatial autoregressive parameter ρ by using the first-order conditions of the likelihood functions of (6) and (9). The spatial parameters $\phi - \alpha\rho$ and $\varphi - \beta\rho$ are the coefficients of the spatially weighted independent variables, which are treated as additional regressors. The substitution of the closed-form solutions into the likelihood functions gives the concentrated likelihood functions with ρ as the only unknown variable. However, $\hat{\rho}$ can be obtained by maximizing the concentrated likelihood function. Hence, all other parameter estimates can be found once we have an estimate of $\hat{\rho}$.¹¹

2.3. Technology Spillovers and Spatial Elasticities

As demonstrated in [LeSage and Pace \(2009\)](#), for spatial models the usual interpretation of the coefficients for the input factors is not valid as the coefficients for inputs in the log-linear equations (4) and (5) are not simple elasticities. LeSage and Pace instead suggest the following approach to calculate direct, indirect, and total marginal effects. We illustrate their approach for the more general SDM model with no biased technical change. Rewriting equation (9) as:

$$\ln y = \Omega(\alpha I + (\phi - \alpha\rho)(W_N \otimes I_T)) \ln k + \Omega(\delta_g r + QU + V), \quad (11)$$

elasticities are found by differentiating equation (11) with respect to per-worker capital, yielding the matrix of direct and indirect effects for each industry, where the right-hand side of equation (12) is independent of the time index:

$$E_k = \Omega \begin{bmatrix} \alpha & w_{12}(\phi - \rho\alpha) & \dots & w_{1N}(\phi - \rho\alpha) \\ w_{21}(\phi - \rho\alpha) & \alpha & \dots & w_{2N}(\phi - \rho\alpha) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\phi - \rho\alpha) & w_{N2}(\phi - \rho\alpha) & \dots & \alpha \end{bmatrix}. \quad (12)$$

The mean direct effect of capital for all the region-sector pairs, which we denote e_k^{Dir} , is the average of the diagonal elements of E_k in equation (12) for the SDM model. The indirect effects of capital, which we denote e_k^{Ind} , is the average row-sum of the off-diagonal elements of E_k in equation (12). The mean total effect of capital is $e_k^{Tot} = e_k^{Dir} + e_k^{Ind}$ ([LeSage and Pace, 2009](#)). In the SAR model, the direct, indirect, and total effects can also be calculated using equation (12) but with the off-diagonal elements set equal to zero. However, in the spatial model the direct elasticity not only includes the non-spatial elasticity α but also the feedback effect from other regions and sectors via the commercial network and captured by the global multiplier. The indirect elasticity refers to the percentage change in industry i 's output due to a percentage increase in the sum of the input across all the other $N - 1$ region-sector pairs. Finally, the

¹⁰ Indeed, as explained by [Parmeter and Kumbhakar \(2014\)](#), we first apply the within estimator to obtain consistent estimates of the input elasticities and then estimated the residuals of the model. These residuals are then regressed on a constant, a time trend, and the square of the time trend for each production unit.

¹¹ A more detail discussion of the algorithm is presented in [Liu and Sickles \(2023, Appendix A\)](#).

calculation of total elasticity is based on all N region-sector pairs in the sample simultaneously changing their own input levels.

In the same way, we can describe productivity change over time and the magnitude of spillovers between the industries through spatial correlation. By differentiating equation (10) with respect to the time trend, the productivity change spillover can be measured by the indirect marginal effect:¹²

$$g_t \equiv \left[\frac{\partial \ln y}{\partial t} \right]_t = \begin{bmatrix} \Omega_{11} \frac{\partial R_t'}{\partial t} \delta_1 & \Omega_{12} \frac{\partial R_t'}{\partial t} \delta_2 & \cdots & \Omega_{1n} \frac{\partial R_t'}{\partial t} \delta_n \\ \Omega_{21} \frac{\partial R_t'}{\partial t} \delta_1 & \Omega_{22} \frac{\partial R_t'}{\partial t} \delta_2 & \cdots & \Omega_{2n} \frac{\partial R_t'}{\partial t} \delta_n \\ \vdots & \vdots & \ddots & \vdots \\ \Omega_{n1} \frac{\partial R_t'}{\partial t} \delta_1 & \Omega_{n2} \frac{\partial R_t'}{\partial t} \delta_2 & \cdots & \Omega_{nn} \frac{\partial R_t'}{\partial t} \delta_n \end{bmatrix}_t, \quad (13)$$

where Ω_{ij} is the (i, j) element of Ω . The diagonal elements of the matrix in equation (13) are the direct effect, which represents the productivity change for region-sector pair i itself at time t . However, the indirect effect has two different interpretations depending on which directions to sum the off-diagonal elements. The row-sum of off-diagonal elements represents the aggregate spillover that each region-sector pair *received* from all of its neighbors through the spatial linkages. The column-sum of off-diagonal elements represents the aggregate spillover that each region-sector pair *provides* its neighbors. In both cases, the compound productivity change for region-sector pair i is the summation of the direct and indirect effects.¹³

3. Data

This paper combines the information of two different databases: BD.EURS and EUREGIO. While the first database contains information on European region-sector pairs' output and primary inputs for the period 1995-2014, the second database allows computing spatial and intersectoral weight matrices for the period 2000-2010. If we use a time-invariant weight matrix (e.g., for the year 2000), a production function can be estimated for the period covered by the BD.EURS database. If we use a time-varying weight matrix instead, we are forced to restrict our sample period to the period covered by the EUREGIO database.

The BD.EURS database contains the basic macroeconomic variables of 121 European regions (NUTS-2), disaggregated by sectors. The sources of information are EUROSTAT, AMECO and EU-KLEMS. More information on this dataset can be found in [Escriba et al. \(2019\)](#) and [Gómez-Tello et al. \(2020\)](#). This dataset contains information on Gross Valued Added (VA) in current and constant prices, Employment (L), and Capital stock (K). The main contribution of this database is the estimation of the capital stock at the regional level. Therefore, this database allows estimating sectoral production functions, like most of the papers using country-level data, but here using regional data. BD.EURS is limited to nine countries for the period 1995-2014. The countries included are Belgium, Germany, France, Italy, The Netherlands, Austria, Portugal, Sweden and Spain. This European regional database provides the previously mentioned economic indicators for six sectors: Agriculture, forestry, and fishing (Sector A); Industry (Sector BCDE); Construction (Sector F); Productive Market Services (Sector GHIJ); Real estate, financial and business services (Sector KLMN); and Non-market services (Sector OU). The summary statistics by country and sector of these variables are shown in [Table 1](#).

[Insert Table 1 here]

¹² We should add the biased component of technical change (i.e. $\beta \ln k$) to $\partial R_t' / \partial t$ to equation (13) if we use a non-neutral Hicks specification of SAR model.

¹³ In [Appendix A](#), we show the expressions of the elasticities of input factors and productivity change spillovers for the Spatial Durbin form of the production function in equation (10).

With this information at hand, we have computed the TFP growth of each region for the whole period 1995-2014, and the restricted period 2000-2010. As these rates of growth are not estimated but computed using a simple (growth) accounting approach, we hereafter label them as “growth accounting TFP.” The TFP of each sector-region pair has been computed by using a common elasticity to weight its input levels, as in [Beugelsdijk et al. \(2018\)](#). These authors compute the TFP growth for each European region using common input elasticities and sector-specific elasticities and find correlation coefficients larger than 98%. The TFP level of each region (country) is computed in a similar fashion but with output and primary input measured at the regional (national) level.¹⁴

For comparison grounds, we have also collected the country-level TFP growth rates provided by prestigious organizations, such as the World Bank (WB), and the Groningen Growth and Development Centre that maintains the well-known Penn World Tables (PWT). [Appendix B](#) depicts the growth accounting TFP evolution of the EU countries using our BDEURS dataset as well as the PWT and WB datasets. In general, the results were quite similar, indicating that our TFP growth rates are comparable to other studies or data sources (only slightly higher in Spain).¹⁵ We have also collected the labor productivity growth rates computed by the WB for nine sectors and aggregated the nine sectors into the same six sectors of our dataset. Again, in general, the figures (not shown for space limitations) are quite similar despite methodological differences and data sources. Finally, we have computed the rates of growth of labor productivity over the period 2003-2014 to compare our growth accounting results with those provided by [Rodríguez-Pose and Ganau \(2022\)](#). Despite not using exactly the same sample period (as we do not have 2015) and using different data sources (WIOD vs. Eurostat), we found very similar growth rates of labor productivity to these authors.

[Figure 2](#) maps the spatial distribution of measured TFP growth across regions in Europe between 1995 and 2014. Most regions witnessed, on average, poor rates of productivity growth. Moreover, many regions experienced negative productivity growth such as the Algarve (Portugal), Asturias (Spain) and Lombardy and Piedmont both in Italy. The highest TFP growth is concentrated in eastern European regions, as well as in Scandinavia, in the same fashion as [Rodríguez-Pose and Ganau \(2022\)](#).

[Insert Figure 2 here]

[Figure 3](#) replicates the above figure for each sector as it maps the growth accounting *sectoral* TFP growth across regions in Europe between 1995 and 2014. We first notice how heterogeneous TFP is present within each region. For instance, while the Industry sector has had a good TFP performance in most countries, the Construction sector has had the worst evolution. As expected, the TFP growth rates in the Agriculture sector are quite heterogeneous. Thus we can conclude that each region has its own tale to tell. For this reason, it is very important to estimate a production model that allows the possibility to obtain very different TFP growth rates for each region and sector. Later we will see whether the proposed specification is sufficiently flexible to capture most of this heterogeneity.

[Insert Figure 3 here]

The second database used in this paper is EUREGIO. This database provides interregional information on imports and exports for 14 sectors (see [Appendix C](#)), which are aggregated into 6 sectors in order to match the sectoral disaggregation used in the other database (i.e. BD.EURS). Using this

¹⁴ In particular, the TFP level of each region-sector pair (i,j) has been computed as $TFP_{it}^j = VA_{it}^j / X_{it}^j$, where $X_{it}^j = (K_{it}^j)^{0.4} (L_{it}^j)^{0.6}$ is a measure of all primary inputs used in region-sector pair (i,j) . Notice that these weights are close to both the elasticities typically used in growth accounting and the elasticities of capital and labor found in our application.

¹⁵ The main differences are found in Sweden. Without this country, the correlation between our TFP growth rates and those computed by the WB is very high (about 88%). The correlation with Sweden is less but still large. The correlation decreases because Sweden's productivity increases much more than the productivity in other EU countries using our data and other data sources, and its performance is thus a bit different than the average performance of other EU countries in terms of rates of growth.

information, we build our inter-regional and inter-sectoral weight matrix (W). Instead of using geographical distance to construct the spatial weights matrix, we extract the input and output flows based on the EU Input-Output tables to measure economic distance between industries within/across NUTS2 economies. 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, [Liu and Sickles \(2023\)](#) advocate using intermediate flows to build the weight matrix because, as an important vector of knowledge diffusion, intermediate flows better represent and reflect communication and cooperation in production among industries.¹⁶ We utilize a spatial weight matrix based on bidirectional upstream and downstream linkages to take into account both the “passive” technology improvement by using advanced intermediate products from upstream suppliers and “proactive” technology improvement from learning by producing innovative intermediate products to downstream customers.¹⁷

To conclude the data section, it should be pointed out that we do not measure the effect of other productivity drivers, such as public investment in infrastructure ([Pereira and Andraz, 2013](#)) or human capital ([Mankiw et al., 1992](#); [Islam, 1995](#)), due to data limitations at either the regional or sectoral level. Properly measuring these effects is also a challenging task. For instance, monetary measures of infrastructure are available at the regional level in Eurostat. However, [Orea et al. \(2023\)](#) state that, while such monetary measures may be adequate for the private sector's capital stock, they can be badly misleading for public capital, as an abundant literature has argued. Regarding human capital, despite often being treated as one of the possible determinants of differences and divergences in regional productivity and income, the empirical evidence is rather inconclusive and no effect of human capital on the economic growth is often found in the literature (see e.g. [Čadil et al. \(2014\)](#); and [Delgado et al. \(2014\)](#) for a comprehensive discussion of the effects of human capital).

4. Results

4.1 Parameter estimates

The baseline empirical model is a Cobb-Douglas production function with only two inputs (capital and labor) and a conventional time-trend variable to account for the effect of technological improvements, the global cycle, or any common factor that affects all regions equally.¹⁸ The time-varying region- and sectoral-specific effects included in all estimated specifications will likely capture the production differences/trends attributable to relevant but unmodeled productivity sources such as public infrastructure and human capital endowment. In keeping with most of the earlier literature, constant returns to scale have been imposed. As [Orea et al. \(2023\)](#) point out, the constant returns to scale assumption not only allows using the capital/labor ratio as an explanatory variable, thus reducing its collinearity with the time trend, but also because most national bureaus of statistics make the industry primary input costs equal to the corresponding industry revenues and the satisfaction of this equality only happens when the production process is characterized by constant returns to scale. We recognize that our empirical strategy based on a

¹⁶ 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](#)).

¹⁷ We have shown in the introduction that there are remarkable commercial linkages across the European regions and sectors. As shown in [Appendix D](#), the inter-regional and inter-sectoral linkages have also increased a lot throughout the 2000s. This appendix contains two figures that map the trade size of each region-sector for 2000 and 2010. The trade size of each region-sector is measured by summing the elements of each row of the weight matrix for 2000 and 2010, respectively. We next divided these two vectors by the 2000-2010 average to get manageable values. Values larger than unity (or reddish colors) indicate that the trade of goods and services at the beginning or the end of the 2000s is larger than the trade observed on average in this decade. Values that are smaller than unity (or bluish colors) suggest the opposite.

¹⁸ We recognize that public investment and human capital are variables normally included in growth models ([Álvarez and Barbero, 2016](#)). However, disaggregated (regional-sectoral) public and human capital stock is not available for European regions, to the best of our knowledge. We try to address this issue by including a set of sectoral-specific effects in the model.

simple but traditional constant-returns-to scale production frontier model with relatively few regressors has been highly conditioned by the data. It should be pointed out, however, that most of our parameter estimates have the expected sign and our results are sound despite (or perhaps thanks to) the lack of sophistication of our production models.

We estimate SAR and SDM spatial specifications of our production model. The SAR model incorporates the endogenous spatial lag of the dependent variable ($Wlny$) as a regressor. As we use a row-normalized W matrix, $Wlny$ can be viewed as a weighted measure of the output of interconnected regions and sectors and the ρ parameter is the spatial autoregressive coefficient that measures the degree of spatial and sectoral correlation between units. The SDM model is an extension of the SAR model that accounts for local spatial interaction through the input usage on neighboring regions and sectors. That is, it includes the spatial lag of capital deepening (i.e., $Wlnk$), and θ is the unknown spatial parameter. Both models have been estimated using a row-normalized W matrix for 2000. Notice that this W matrix does not change over time. Changing the time-invariant W matrix does not produce significant changes in the parameter estimates.¹⁹ Here it is important to highlight that even though the estimated coefficients in our application for 2000-2010 were quite robust to using time-varying or time-invariant W matrices, one of our simulation exercises is devoted to illustrating the output effect of changes in trade network (measured as a change of the W matrix from 2000 to 2010). Our analysis shows a clear heterogeneity in the results both by regions and by sectors.

We use a symmetric W matrix that aggregates both downstream and upstream flows of intermediate goods. As is customary in the spatial econometric literature, this matrix is row-normalized with the row-sum of intermediates. This is consistent with a productivity network wherein spillovers are dependent on the share weighted sum of the productivity of their intermediate partners (Coe and Helpman, 1995). Tiefelsdorf et al. (1999) point out that this standardization procedure may overstate the role of units with fewer connections in the spatial network. Plümper and Neumayer (2010) also point out the importance of the functional form for the weighting matrix. As TFP is a relative concept, defined as a ratio of outputs and inputs, the row-normalized W matrix conforms to the homogeneous characteristics of the production function commonly used in the literature. Row-normalization is also more consistent with the arguments demonstrated by general equilibrium models in the production network literature (Acemoglu et al, 2012; Baqaee and Fahri, 2020). Moreover, our empirical findings are much more robust to model specification using a row-normalized W matrix rather than a weight matrix that uses the alternative maximum eigenvalue normalization. Our estimates based on both FE and RE methods are quite comparable using a row-normalized W matrix for both SAR and SDM specifications. However, when we estimated the same models using the eigen-normalized W matrix, the coefficients of the spatially lagged variables changed dramatically.²⁰

We have also analyzed results based on the pre- and post-financial crisis periods 1995-2008 and 2009-2015.²¹ We found that the elasticity of capital deepening (the coefficient of lnk), was smaller during the pre-crisis subperiod and larger during the post-crisis subperiod, indicating the existence of important structural changes in sectors' production processes caused by the financial crisis. To control for non-neutral effects of common factors that affect all regions, we estimate two alternative specifications of the baseline model, depending on whether or not we interact the time trend with the capital/labor ratio. Much of the differences in lnk estimates between these sub-periods are in the cross-section dimension of the data.

¹⁹ We also use time-varying spatial weight matrices to consider the evolution of network from 2000 to 2010. Appendix E shows the RE parameter estimates using time-varying W matrices. The coefficients estimated are also consistent with the time-invariant spatial weight matrix results.

²⁰ But the shortcoming of row-normalization is that it cannot represent the change of the spillover across time, even if we use a time-varying W matrix. This is because this normalization strategy eliminates both the growth of off-diagonal elements across different periods and the differences in trade size across regions and sectors.

²¹ The parameter estimates of these two subperiods are available upon request from the authors.

Therefore, the non-neutral specification simply suggests that technical change is no longer common to all observations and that it is larger in regions/sectors with greater capital deepening. There are only minor differences in the estimated TFP growth rates with and without this interaction. This would suggest that the flexibility of our specification provides quite comparable estimated TFP growth rates even if we are not controlling for the non-neutral portion of technical change. However, even though the total TFP estimate may be correct, its drivers may be misunderstood without the sort of modeling detail we have provided, in this case the possibility of biased technical change.

We have estimated our production models using FE and RE estimators. We chose to use an RE model for several reasons. First, we could not reject the RE model for SAR and Durbin specifications of our production model, notwithstanding the relatively low power of the test (Clark and Lizner, 2014). Second, the RE model has the advantage that it can capture both the between and the within variation of the data while the fixed effect model only captures the within variation of the data (Fageda, 2014). In our empirical model, the explanatory variable is the ratio of capital to labor that has a low within-variation in our short panel dataset. It is well known in the literature that a shortcoming of the FE model is that it cannot identify the effect of variables that do not change over time or have a low within variation. We recognize that a disadvantage of the RE model is the potential bias derived from the correlation between the explanatory variables and the error term. We find however that both FE and RE models yield very similar coefficients for the time-varying regressors. We also found very similar TFP growth rates for both FE and RE estimators. The choice between FE and RE estimators is not a crucial issue in our empirical findings. However, in our simulations the use of dummy variables FE specifications are quite unwieldy and add computational burdens that are rather severe. We thus use results based on the RE specification of our production frontier in order to carry out our simulation exercises and thereby discuss our corresponding empirical findings.

Table 2 shows the RE parameter estimates using SAR and SDM specifications. All estimates include regional and sectoral-specific effects that are not reported in this table for space limitations.

[Insert Table 2 here]

All the coefficients for the factor inputs in the SAR and SDM specifications are statistically significant at the 1% significance level. The four models yield similar results regarding the output elasticities of labor and capital. The direct effect of both inputs follows conventional growth accounting, a labor elasticity of around two-thirds, and a capital elasticity of around one-third. The time-varying elasticity models show that the elasticity of capital (labor) input is increasing (decreasing) over time as the coefficient of the interaction of lnk with the time trend is in the range of 0.005 to 0.008. We already found this result when we split the sample into pre- and post-crisis periods. The increasing marginal product of capital relative to labor is consistent with studies of productivity in general and the impacts of capital deepening on labor, income and within-country inequality (see e.g. Weil, 2015).

Evidence of the existence of global spatial spillover effects from neighboring regions and sectors is found in all models. The coefficient of the spatially lagged dependent variable ρ is estimated in a range of 0.386 to 0.417. Therefore, the income level of neighboring regions or sectors positively affects economic growth, in accordance with other studies using regional data (see e.g. Gude et al., 2018 and Arbues et al., 2015 for the Spanish provinces). The SDM model also allows the introduction of local spillovers. The parameters ϕ , which represent the local spatial relationships of factor inputs can be calculated based on the expressions in equation (9). The estimates of ϕ in the SDM are 0.229 and 0.232 for the time-invariant and time-varying elasticity specifications, respectively. Therefore, the spillover effects related with the capital deepening of both neighboring regions and sectors are positive using either neutral or non-neutral specifications for technical change. Notice that, in the time-varying elasticity specification, the spillover effects associated with capital deepening decreases over time because the coefficient of the interaction of $Wlnk$ with the time trend is slightly negative but statistically significant. A negative coefficient might be indicative of increasing Myrdal's backwash effects (Myrdal, 1957), which may arise through competition

in production factors between provinces. This would be an indirect corroboration of the existence of agglomeration economies drawing production factors to locations with greater economic activity reinforcing the theories explaining core-periphery patterns (Barbero and Zofío, 2016).

It is germane to mention at this point that, as the computed parameter ϕ is positive, our results are in line with Arrow-Romer's physical capital externalities (Arrow, 1962; Romer, 1986). Note, however, that, as our models in Table 2 were estimated using the CRS assumption, we also find evidence of negative spillovers related with the other production factor (i.e. labor). This suggests that the increased usage of labor in the neighboring (supplier or customer) industries appears to have a negative effect on the industry itself because of the scarcity in labor force. This might be indicative of Myrdal's backwash effects in the usage of labor which may arise through competition for the employed labor force between regions and sectors. Moreover, the negative coefficient found for $Wlnk \cdot t$ (i.e. the positive coefficient found for $WlnL \cdot t$) suggests that the competition for this production factor has decreased over time in our application, an expected result due to the financial crisis causing further unemployment and hence less scarcity in labor force.

Interestingly, the coefficient for $Wlnk$ changes substantially if we compare the RE estimates in Table 2 and their FE counterparts shown in Appendix F. It also varies notably if we split the sample into pre- and post-crisis subperiods. On the other hand, the sign of this coefficient also seems to depend on the selection of a time-varying vs time-invariant W matrix, or on whether we use row-normalized and eigen-normalized W matrices.²² As the coefficient of $Wlnk$ has proved to not be very robust for our model specification, we select the SAR specification to compute direct and indirect effects and to carry out our simulation exercises.

4.2. Technical change

We have included a conventional time trend in our model as a placeholder to summarize common shocks. The coefficients of the time trend variables are significant and negative for all specifications, indicating that the economic environment has worsened over time, reducing regions' productivity.²³ Notice that while the estimated coefficients for the time trend are statistically significant, they are smaller when assuming neutral technical change. The estimated coefficients for t increase notably when we use a non-neutral specification. Considering that TFP growth can be decomposed into the neutral and capital-enhanced technological progress, if non-neutral technical change is assumed, this seems to suggest a larger deterioration of regions' productivity attributable to common economic shocks. The coefficient of $lnk \cdot t$ allows us to qualify this result even further. The positive coefficient found for this interaction suggests that, on average, the regions and sectors with larger capital-labor ratios have suffered less from the economic environment deterioration.

The non-neutral SAR model also allows us to investigate heterogeneity within the same sector and between different sectors by computing the output elasticity with respect to the time trend variable.²⁴ We find clear heterogeneity in the results induced by differences in factor proportions and capital deepening. Figure 4 illustrates this heterogeneity by sector. We find on average negative rates of technical change in all sectors, except in RSFB Services which has the highest capital-labor ratio in the data, and hence the largest rate of technical change (with $TC = 0.4\%$). The worst performance is found in Construction (with $TC = -1.2\%$) as it has the lowest capital deepening. Figure 4 also shows remarkable within-sector

²² The parameter estimates of the models with eigen-normalized W matrices are available upon request from the authors.

²³ We also estimated our models adding the square value of the time trend, but its coefficient was insignificant and negative. A negative value is quite unreasonable because it means that the TFP growth is decreasing at an accelerating speed. We also estimated the above models with time dummies, but they proved to be insignificant as well.

²⁴ As pointed out in a previous footnote, the CSS method also permits different rates of TC for each sector. In this frontier setting, we also find negative rates of TC for each sector, except for the Industry sector.

heterogeneity in technical change. According to the standard deviation statistic, the largest heterogeneity is found in the Agriculture sector, followed by the Construction sector. Interestingly, the most homogeneous rates of technical change are found in the three ‘services’ sectors.

[Insert Figure 4 here]

4.3. Input elasticities.

The coefficients of the independent variables represent the output elasticities of input factors in a non-spatial production function setting. However, when cross-sectional interactions exist, the output change of one industry due to the adjustment of the factor input is complemented by induced changes in its neighbors’ inputs. Hence, an elasticity in a spatial setting includes two parts: the internal elasticity expressed by a direct effect, and the external elasticity measured by an indirect effect. Total output elasticity can thus be expressed by the sum of the direct and indirect effects. Table 3 shows the direct, indirect, and overall effects of capital and labor that can be computed using the SAR specification.

[Insert Table 3 here]

The internal elasticity of capital is 0.411 and statistically significant using a Hicks neutral specification of technical change, which is approximately consistent with the results that we get using a non-spatial model.²⁵ The external elasticities reflect the spillover effects of the capital deepening from neighboring industries. Table 3 shows that there is a significant indirect effect (0.274) of capital when we use a time-invariant elasticity, which suggests that a sector’s technological upgrading may benefit from trading with neighboring industries with high organic composition of capital. Similar comments can be made if we use a time-varying elasticity specification. However, in this case, the elasticities of input factors vary over time due to the interaction of *lnk* with the time trend. We find that both the direct and indirect elasticity of capital increased markedly over the two decades examined in this paper. Indeed, if we use a SAR specification, the direct (indirect) elasticity of capital ranges from 0.3920 (0.2717) in 1995 to 0.494 (0.3420) in 2014.

Including the spillover of factor input, the overall elasticity of capital is much higher (0.685 and 0.655) than in a non-spatial model. In other words, the non-spatial models underestimate markedly the “true” elasticity of capital in our application. Moreover, the non-spatial models also overestimate the productivity growth when inter-regional and inter-sectoral spillover effects are ignored. Indeed, while the coefficients of the time trend in a SAR model with time-invariant and time-varying elasticity are respectively -0.005 and -0.032, their non-spatial counterparts are respectively -0.002 and -0.026. The coefficient of the time trend here only represents the common internal productivity growth in our sample. We will discuss this further along with the role of spillovers in section 4.4.

4.4. TFP growth

We have also calculated region and sector-specific productivity growth rates using the random effects SAR model. Following Balk (2016a), the individual TFP growth rates are next aggregated in order to measure regional TFP change.²⁶ It is well-known in the literature that the simple weighted mean of region-specific TFP changes (*within* effect) provides a biased measure of regional TFP change if the within-region relative sizes of each sector do not change over time, i.e. when the so-called *reallocation or shift-share* effect is not negligible.²⁷ Fortunately, we have found in Figure 1 that, in our application for the European regions, the reallocation effect is quite small compared to the within effect. Therefore, we will

²⁵ The non-spatial counterparts of our RE models are shown in Appendix G. These models were estimated using the method developed by Cornwell et al. (1990).

²⁶ Following Balk (2016a), the individual TFP growth rates are weighted using value-added shares (see Appendix H).

²⁷ The reallocation effect should not be ignored even if we were using Domar's weights (see Jorgenson et al., 2007 eq. 31).

not be far from the aggregate TFP growth rate when we compute regional TFP growth using a weighted average of our estimated TFP growth values for each region-sector.

Like the input factors, in a spatial setting we can compute direct, indirect, and total TFP growth rates from both offered and received directions. [Figure 5](#) maps the estimated total TFP growth from the received direction for each region-sector pair for the period 1995-2014, when they are computed using the SAR model with time-invariant elasticity, with the weight matrix not changing over time. As approximately the same maps are obtained if we use a time-varying elasticity specification of the model, we do not discuss the time-varying elasticity results. In other words, as our estimation strategy is highly flexible, we do actually identify very similar productivity trends despite finding remarkable differences in technical change induced by differences in capital deepening across sectors and regions (see [Figure 4](#)).²⁸ The region and sector-specific values, and standard errors, can be found in [Appendix I](#).²⁹

[Insert Figure 5 here]

The first feature of [Figure 5](#) that should be highlighted is its close resemblance with the previous figure. That is, both measured and estimated TFP growth rates are highly correlated (the correlation is larger than 90%), indicating that our econometric model is flexible enough to capture most of the heterogeneity found using a growth accounting approach to measure region and sector's TFP growth. Therefore, this figure again indicates that the industry (construction) sector has had the best (worst) TFP performance, and that the agriculture sector is quite heterogeneous. The attenuated reddish colors and the more powerful blueish colors in [Figure 5](#) suggest, however, that we are in general underestimating a little the TFP growth measured using a growth accounting approach, an issue that will be discussed in detail later.

We next decompose the total TFP growth rates into their direct and indirect components. [Figure 6](#) maps the estimated direct TFP growth. Notice that this figure looks like [Figure 5](#). This implies that the overall TFP performance in most sectors has to do with within-industry factors. [Appendix I](#) shows that 64.3% of the direct effects are negative and statistically significant. For this reason, the blueish color is the most predominant color in [Figure 6](#). In the case of the industry sector, this implies that most of the relatively good TFP performance found for this sector in [Figure 5](#) can be explained by favorable factors occurring within both the same industry and region. The opposite statement can be made in the case of the construction and real estate, financial and business services sectors. Their TFP decline in [Figure 5](#) is mainly caused by negative within-industry and within-region factors that have pulled down their overall productivity. The largest direct effect (5.4%) is found in Groningen (Netherlands) followed by Stockholm (Sweden). They are also noteworthy in Brabant Wallon (Belgium), in three Spanish regions (Basque Country, Castille-La Mancha and Extremadura), in two German regions (Brandenburg and Sachsen-Anhalt), and one Italian region (Basilicata). The significant heterogeneity evident in the figures can be attributed in part to the sectoral composition of the regions, which influenced their exposure to the financial crisis of 2009. This impact was particularly pronounced in sectors such as Construction, Real Estate Activities, and Financial Services, which experienced substantial drops in TFP. Notably, Portuguese regions, certain Southern Italian regions (especially those along the Adriatic coast), and some Spanish regions all exhibited negative TFP growth across all sectors during the given period. Focusing on the Industrial sector, where TFP growth is positive for most regions, we observe a concerning situation for some Italian and Portuguese regions. Even

²⁸ Similar conclusions can be inferred from a model that uses a time-varying weight matrix because, despite the network of regional trade flows changing over time (see [Figure 1](#)), the regional trade flows vary only moderately on an annual basis. The equivalent maps and the region and sector-specific values are available on request from the authors. In any event, they only allow an examination of the TFP performance from 2000 to 2010.

²⁹ We estimated the standard errors of each direct/indirect effect coefficient by adding the variance of 726 individual productivity growths into the variance-covariance matrix by Lesage and Pace. Given the complicated covariance structure of the spatial model and so many direct-indirect coefficients, the bootstrap simulation considered the variance of individual productivity growth and the variance-covariance of other parameters but did not consider the covariance of the 726 individual productivity growths with the other parameters such as ρ and σ^2 .

in this sector, these regions do not show increases in the TFP. And this not only highlights the persistent regional disparities within Europe but also sheds light on the long-term economic stagnation experienced by specific regions (Diemer et al., 2022).

[Insert Figure 6 here]

Figure 7 maps the indirect TFP growth from the received direction. 97.8% of the indirect-received effects are statistically significant: 27.8% are positive and 70% are negative (see Appendix I). For this reason, the blueish color is again the most predominant color in Figure 7, indicating that the entire commercial network has often had a negative impact on each individual sector. This implies, for instance, that the good TFP performance of the industry sector has been (slightly) attenuated by factors located in other regions/industries. Additionally, it highlights that the declines witnessed in the construction and real estate activities sectors have offset the positive spillover impacts. It is also worth mentioning that east Germany received moderate positive spillovers from their trading partner industries in most sectors. In contrast, the large number of white colors in the agriculture sector suggests that the indirect effect has proved only slightly positive for many regions in this sector. Therefore, the indirect effect in the agriculture sector has attenuated the overall TFP reduction observed in some (e.g. German) regions or stimulated the observed TFP improvement in some French, Spanish or Swedish regions. In the other sectors, the indirect effects have accentuated the overall TFP decline.

[Insert Figure 7 here]

Figure 8 maps the indirect TFP growth from the offered direction. The interesting comment here is that the offered indirect effects toward partner firms are fairly large in the industry sector, while the received effects were much smaller. The offered indirect effects are even larger than 5% in Groningen and Stockholm. They are also notable in three Spanish regions (Basque Country, Castille-La Mancha and Valencia), two adjacent German regions (Sachsen and Sachsen-Anhalt) and two French regions (Île de France and Provence-Alpes-Côte d'Azur). In all these regions, the indirect offered effect is larger than 3%, but smaller than the effect found in Groningen (due to its important energy sector) and Stockholm.

[Insert Figure 8 here]

4.5 Efficiency scores

We examine in this subsection the spatial distribution of the computed regional and sectoral efficiency scores. They were obtained using the procedure introduced by Cornwell et al. (1990) in a non-spatial setting. As our SAR model allows us to estimate time-varying individual effects, the same procedure can be used to obtain efficiency scores in a spatial setting. We should note that this involves a normalization of the productivity estimates after the model is estimated and thus our parameter estimates are not leveraged by parametric distributional assumptions on the stochastic spatial panel frontier.

The estimated efficiency scores should be interpreted in a broad sense. Obviously, they might capture differences in technology or in technical inefficiency across sectors and regions. However, the inefficiency scores are likely capturing differences in other factors that tend to reduce the competitiveness of an industry or sector to the benefit of others. For instance, Orea et al. (2023) point out that a wide variety of distorting regulations, size-dependent policies, financial constraints, trade restrictions, and other market frictions (Restuccia and Rogerson, 2013) might prevent the equalization of marginal products across firms, and thereby cause aggregate output and total factor productivity to fall short of their efficient levels. Therefore, our sectoral inefficiency might also capture production losses stemming from the inefficient allocation of resources across firms operating in the same industry. Other studies, for instance, emphasize the significant role of government quality and human capital in European regions' economic development (Rodríguez-Pose and Ketterer, 2020, Rodríguez-Pose and Ganau, 2022; Álvarez et al. 2023).

Table 4 shows the descriptive statistics of the Cornwell, Schmidt, and Sickles (CSS) and SAR efficiency scores by sector for the 1995-2014 period. Both models assume (non-spatial) time-varying factor

elasticity and were estimated using an RE estimator. It is first worth noting that the non-spatial (CSS) model tends to yield larger efficiency scores than the spatial (SAR) model. As we cannot reject the existence of inter-regional and inter-sectoral spillovers in our application, this indicates that the CSS model overestimates the efficiency scores of the European regions and sectors. Moreover, we also found that both the CSS and SAR efficiency scores are poorly correlated with the coefficient of correlation between them proving to be only 37%. Therefore, a non-spatial specification that ignores the existence of spillovers via the commercial network may incorrectly rank European regions and sectors in terms of their relative efficiency.

[Insert Table 4 here]

The average efficiency score using the SAR model is rather low at 46.7%. It increases to 58.3% for the non-spatial CSS specification. An advantage of the CSS approach is that it is based on the OLS estimates from a panel model specification and does not use a parametric distribution approach to identify efficiency scores for a particular observation. However, since the [Cornwell et al. \(1990\)](#) device used to estimate observation-specific inefficiency relies on order statistics, specifically the “max” operator (see for example, [Green, 1980](#); [Wang and Schmidt, 2009](#)), its robustness for outliers is questionable. Outliers appear to be evident in the industry sector where the average efficiency score is 23.6% using our SAR specification. This relatively low score is basically caused by the extremely large individual effect found for Groningen in this sector.³⁰ If we compute the average efficiency score in the industry sector without Groningen’s individual effect, the score increases to 50%. To not mislead the efficiency analysis of this sector, we hereafter use the last set of efficiency scores.

[Figure 9](#) maps the average SAR efficiency scores by sector. The largest efficiency scores in the agricultural sector are found in southwest Europe: Murcia (Spain), Champagne-Ardenne (France) and Alentejo (Portugal). It is worth mentioning that most regions in the Iberian Peninsula have rather high agricultural efficiency scores. Regarding again the industry sector, in addition to Groningen, we also find remarkable efficiency scores in Brabant Wallon (Belgium) and Sachsen-Anhalt (Germany). Most of the efficient regions in the construction sector are in France (e.g., the Centre, Lower-Normandy, and the Bourgogne) and Netherlands (e.g., Drenthe and Overijssel). High efficiency scores are also found in central Europe and Sweden. The lowest scores in this sector are found in Spain, especially in the two Castille regions. The best performance in Market Services is in central Europe, especially in Vienna (Austria) and Berlin (Germany), as well as in two regions of Netherlands (Flevoland and Utrecht). The highest efficiency scores in real estate, financial and business services are found in Hessen (Germany) and three Italian regions (Emilia-Romagna, Tuscany, and Marche). Except for Brussels, the highest efficiency scores in non-market services are found in south Europe, in four Italian regions (Lazio, Abruzzo, Molise and Marche) and three Portuguese regions (the North, Lisbon and the Algarve).

[Insert Figure 9 here]

4.6. Robustness analyses

In this subsection, we examine the robustness of the spatial (SAR) model used previously to compute (in)direct effects and to carry out the simulation exercises shown in [Section 5](#). It includes three analyses. In the first one, we examine whether the input elasticities of our Cobb-Douglas production function vary across countries. Our findings support the existence of heterogeneous elasticities across countries. Despite this, our most significant result here is that our TFP growth rates fall within the range of those estimated previously using a model that does not allow for country-specific input elasticities.

³⁰ The Groningen region of the Netherlands region had a large gas extraction company that grew quite substantially during our sample period. World natural gas prices increased by almost 350% during this time. (<https://www.creditdonkey.com/gas-price-history.html>).

In the second analysis, we again estimate our Cobb-Douglas production model but, in this case, without the constant returns to scale (CRS) assumption. We might have overestimated (underestimated) the changes in TFP if underlying (dis)economies of scale are ignored. We examine this issue by undertaking our estimation using Variable Returns to Scale (VRS) technology. The estimated input elasticities are then used to compute a TFP growth measure that includes a size-related effect associated to changes in the usage of inputs, in line with [Orea et al. \(2024\)](#). We find that the VRS-based TFP growth rates are of the same order as our previous CRS-based TFP growth rates, but now most of the poor TFP performance is attributed to increases in the usage of inputs given that VRS technology is characterized by large diseconomies of scale.

Finally, in the third analysis, we examine whether our TFP results are robust to using a more flexible specification of our production function. In this case, also as suggested by a reviewer, we estimate our production model using a Translog form. This specification not only allows for heterogeneous elasticities across countries, but also across sectors and over time. Our findings support using a specification with second-order coefficients for our production function. However, again, our TFP growth rates fall within the range of those estimated previously using a Cobb-Douglas specification.

In summary, the next set of robustness analyses extend the SAR Hicks-neutral production function used in our previous sections by estimating: i) a Cobb-Douglas production function with heterogeneous input elasticities; ii) Cobb-Douglas production function with variable returns to scale; and iii) a Translog production function that adds quadratic terms to our Cobb-Douglas model but still keeps the CRS assumption.³¹ In general, we find that our TFP results are robust to several modeling specifications of the production function.

4.6.1. *Country-specific technologies*

In this subsection, we estimate a constant-returns-to-scale Cobb-Douglas production model with country-specific input elasticities, as suggested by a reviewer. The estimated parameters are shown in [Appendix J](#). The first model shown in this appendix coincides with the first model in [Table 2](#) and hence it assumes a common elasticity of capital deepening for all countries. The second model allows for heterogeneous (i.e. country-specific) elasticities and shows that the coefficient of $\ln k$ indeed changes across countries as it ranges from 0.182 to 0.664. However, the average elasticity found using this model (0.453), is close to that found using a simpler specification with a common elasticity for all countries (0.407) and consistent with the labor (capital) share in Europe. Note also that a model allowing for country-specific coefficients allows us to identify two countries with relatively large elasticities of capital input (France and Sweden) and three countries (Germany, Netherlands and Spain) with a remarkable elasticity of labor input. If we interpret these elasticities as input shares, these results might indicate that the relative prices of both labor and capital favor the use of capital in France and Sweden and the use of labor in Germany, Netherlands and Spain.

We next examine the impact of this issue on our TFP growth rates. The impact can be evaluated by visually comparing the distributions of our TFP growth rates, or by testing whether both distributions are equivalent using a Kolmogorov-Smirnov (KS) test. [Figure 10](#) compares several distributions of TFP growth rates. Panel a) of the figure displays the distributions of our TFP growth rates for the models with common and country-specific elasticities. We observe that the kernel densities of both distributions are very similar. The null hypothesis that the two sets of TFP growth rates are drawn from the same distribution cannot be rejected using the KS test.³² Therefore, our previous TFP growth rates are robust to neglecting the existence of heterogeneous elasticities across countries in a Cobb-Douglas setting.

[Insert Figure 10 here]

³¹ Unfortunately, we were not able to estimate a Translog model with VRS.

³² The p-value for this is 0.273, which is not significant.

4.6.2. VRS vs CRS technologies

In our second robustness analysis, we estimate our Cobb-Douglas production model without imposing the constant returns to scale assumption. That is, we estimate here a VRS technology using a Cobb-Douglas function. The estimated parameters are shown in [Appendix K](#). Again, for comparison grounds, the first model shown in this appendix coincides with the first model in [Table 2](#), but now it is expressed in terms of both labor and capital inputs. The second model relaxes the CRS assumption of the previous Cobb-Douglas model.

Although a VRS specification is better from the perspective of statistics, we still prefer using a CRS production model for several reasons. First, the sum of elasticity of capital and labor in the VRS specification of the Cobb-Douglas model is much smaller than unity, indicating that the VRS technology is characterized by large diseconomies of scale. Moreover, the estimated scale elasticity is close to 0.64, indicating that most countries have far exceeded their optimal size. That is, the estimated returns to scale are far from being plausible. Second, [Zelenyuk \(2024\)](#) has recently provided a solid theoretical justification for the use of a CRS technology at macro-level or industry-level.³³ Finally, we also prefer the CRS assumption because most national bureaus of statistics make the primary input costs equal to the corresponding revenues and the satisfaction of this equality only happens when the production process is characterized by constant returns to scale.³⁴

As the CRS specification forces the elasticities to sum unity, our TFP growth rates might underestimate the “true” TFP growth. Note also that the output growth that is not explained by changes in the usage of labor and capital cannot be interpreted as a *pure* TFP growth measure if the technology exhibits decreasing or increasing returns to scale. That is, we must add a scale (size) effect associated to changes in the usage of inputs to the VRS-based productivity growth (see e.g. [Orea et al., 2024](#)), if we aim to compare the productivity growth rates of both the CRS and VRS specifications.³⁵

Panels b) and c) of [Figure 10](#) depict, respectively, the distributions of our original (unadjusted) productivity growth rates and next these distributions once the VRS productivity growth has been adjusted by adding the scale effect, separately for the CRS and VRS models.³⁶ According to the results presented in panel b), as expected we observe that the TFP growth rates of the CRS specification are indeed smaller than the TFP growth rates of our VRS specification. The null hypothesis that the two sets of TFP growth rates are drawn from the same distribution can be rejected using the KS test.³⁷ Interestingly, panel c) of [Figure 10](#) shows that, once we add the scale effect to the VRS productivity growth, both CRS and VRS specifications provide similar results. Now, the null hypothesis that the two sets of TFP growth rates are

³³ In particular, this author shows that the Minkowski-type aggregation of regular individual technologies implies that the aggregate technology will be approximately convex-CRS technology.

³⁴ We have also estimated our SDM model using a VRS specification in order to distinguish between capital and labor spillovers. The estimated parameters are shown in [Appendix L](#). Again, for comparison grounds, the first model shown in this appendix coincides with the neutral Hicks specification of SDM model in [Table 2](#), but now it is expressed in terms of both labor and capital inputs. The second model relaxes the CRS assumption of the previous SDM model. This model permits distinguishing between capital and labor spillovers because it estimates two different coefficients for $WlnK$ and $WlnL$. The VRS specification of our SDM again indicates that, while the growth in physical capital of neighboring industries contributes to the output growth of the industry itself, the spillover effect of labor is negative but not as large as the spillover effect of capital.

³⁵ Indeed, if we express the production function as $Y = f(L, K, t)$, we can write the changes in production as $\dot{Y} = \beta \dot{X} + \beta_t$, where $\beta = \beta_L + \beta_K$ is the scale elasticity, $\dot{X} = [(\beta_L/\beta)\dot{L} + (\beta_K/\beta)\dot{K}]$ can be interpreted as the change of an aggregate input measure, and β_t is the rate of technical change. [Orea et al. \(2024\)](#) next define TFP as output (Y) divided by aggregate input (X) and show that TFP changes can be decomposed as $T\dot{F}P = (\beta - 1)\dot{X} + \beta_t$, where $(\beta - 1)$ is a measure of the returns to scale. This equation thus decomposes TFP growth into a size effect associated to an increase in the usage of inputs plus the effect of other productivity drivers (in our case, technical change).

³⁶ Similar panels are obtained if we use Hicks-nonneutral specifications of the models used to compute this figure.

³⁷ The p-value for this is 0.000, which is significant at any level.

drawn from the same distribution cannot be rejected using the KS test.³⁸ This seems to suggest that neglecting the existence of variable returns to scale in our application is not an important issue when measuring region-sectors' TFP growth.

4.6.3. Flexible production function.

In this third subsection, we estimate a Translog production function, which simply extends our previous Cobb-Douglas specification by adding second-order coefficients. As our preferred Cobb-Douglas specification, the Translog model is estimated using the CRS assumption.³⁹ The estimated parameters are shown in [Appendix K](#), along with the parameters of the Cobb-Douglas models with CRS and VRS. The first-order coefficients of both the labor and capital inputs are positive and significant. Therefore, our average elasticities are robust to including squared terms and interactions among the production factors. Note, however, that we can reject that the second-order coefficients are simultaneously equal to zero. This implies that our labor and capital elasticities are again heterogeneous across countries (and across sectors and over time).

We next examine whether our Cobb-Douglas TFP growth rates are robust to using more flexible specifications of our production function. The distributions of our TFP growth rates using Cobb-Douglas and Translog forms are illustrated in Panel d) of [Figure 10](#). From the inspection of this panel we see that we again find that our Translog TFP growth rates fall within the range of those estimated previously using a Cobb-Douglas specification. That is, Panel d) of [Figure 10](#) verifies that our TFP growth results are robust to using higher-order production factors. The KS test confirms this conclusion as it does not reject the null hypothesis that the Translog and Cobb-Douglas TFP growth rates are drawn from the same distribution.⁴⁰

5. Simulation of transmission shocks

As explained by [Kenourgios and Dimitrou \(2015\)](#), propagation impacts and contagion effects can vary significantly from region to region due to several factors. Among them, sectors within regions diverge with regards to their presence in trade networks and global value chains, with some sectors being more orientated towards local markets (generally services) and others towards export markets. This means that certain sectors are going to receive and transmit external shocks more intensely than others. Hence, the industrial composition plays a crucial role in determining the overall impact in a region. Moreover, industrial structure varies across regions, and the importance of each sector differs from one region to another. More developed regions tend to exhibit greater diversification and are positioned at the center of the trade networks compared to less developed regions. This complexity results in a map of interactions between sectors, where regional external dependences can vary considerably.

Precisely, in this section, through the following four simulations, we show the way this complex system of sectors buying from and selling to other sectors, within and outside the regions, translates into notable differences in regional productivity change. As explained earlier, employing the SAR specification results to compute both direct and indirect effects, we carry out a series of simulation exercises with the aim of illustrating how the model captures propagation effects whilst also emphasizing the significance of spillovers and commercial links in explaining regional productivity. Among other simulations, we present the output changes attributable to the change in the trade network between 2000 and 2010, symmetric and asymmetric shocks resulting from the onset of the 2009 financial crisis and the results of a TFP

³⁸ The p-value for this is 0.139, which is not significant.

³⁹ The input variables have been expressed in deviations with respect to the sample mean in order to interpret the first-order coefficients of the Translog production function as elasticities evaluated at the sample mean, which can be directly compared with those estimated using a Cobb-Douglas specification.

⁴⁰ The p-value for this is 0.965, which is not significant.

improvement due to digitalization. [Appendix M](#) outlines the procedure used to compute all the latter simulations.

5.1. Output changes due to the progress of the trade network.

This first simulation aims to capture the effect of the trade network by changing only the spatial weighted matrix (ΔW) from the year 2000 to the one at the end of the period considered (2010), while keeping all other variables constant. Using the results from the time variant spatial weighted matrix model, we can observe whether the situation of the sector within a region becomes more or less favorable in 2010 compared to 2000 in terms of its position in the production and trade chains. A positive impact on the sector in a region indicates that by the end of the period, it was more engaged in trade than at the beginning, thus also being more exposed to external shocks (both positive and negative) than before. If the opposite happens, the figure indicates that the region is experiencing a decline in its presence in the trade network. In this way we quantify how important the changes are in the structure of the trade network in terms of annual changes in percentages of GDP. This first simulation does not account for the effects of changes in trade size since we are avoiding any scale impact by means of the row normalization⁴¹.

The map in [Figure 11](#) suggests a clear heterogeneity with respect to the results across both regions and sectors. This means that, in contrast to the results obtained for the W time invariant model presented, there is indeed a change in the structure of the network, and these changes are significantly impacting regions in different ways.⁴² In line with this, the warmer colors on the map represent positive annual growth rates and, therefore, regions that have increased their presence in the trade chains by 2010. In contrast, the cooler colors reflect negative values, indicating regions that have experienced a decline in their position within the network.

[Insert Figure 11 here]

By sectors, between 2000 and 2010, a pattern can be observed where the most positive numbers appear for services in general, while tradable sectors (Agriculture – A, Industry – BCDE, and Construction – F) exhibit more extreme values. This phenomenon can be attributed to at least two different forces operating at the same time: first, the development of the trade network has aggravated the gap between the regions in the central and peripheral area of the trade network and the divergence performs differently between sectors. Tradable sectors such as agriculture and industry diverge more notably than service industries ([Ariu, 2016](#)). Second, a continuous trend of tertiarization has occurred in Europe, and thus the service industry has deeply penetrated into the trade network ([Baldwin et al., 2023](#)).

Geographically, we find many differences among regions, which can be divided into three different categories or groups: 1) Regions that improve in 2010 due to the changes in the trade network. This includes the cases of most French, Belgian and Dutch regions, Southern regions in Italy, various sectors in Portuguese regions, and specific sectors in Spanish and Austrian regions. 2) Regions that remain relatively unchanged or with very small impacts. Examples include German regions, Northern Italian regions, and the Île-de-France region where Paris is located). 3) Regions that are worse than in 2000. This is true of the Construction sector (F) in Spanish regions (that was hit hard by the financial crisis) and which displays the lowest annual growths rates in this group. In conclusion, it appears that sectors in regions that were already situated at the core of the trade network in 2000 (Germany, South of Sweden, Austria, Northern Italy and

⁴¹ Of course, regional differences were found also when simulating the effects of trade change considering the change in total trade between regions (size effects). A 1% increase in trade (excluding domestic effects) results in a substantial impact in the industry sector (BCDE), indicating the importance of this sector in the for the propagation and transmission mechanisms affecting regional productivity changes.

⁴² Which essentially reflects that changes in trade and productive structures typically occur in extended rather than on an annual basis, except in cases of significant shocks. In [Kitsos et al. \(2023\)](#), covering the same period 2000-2010, it is shown how the trade structure remained more or less stable during those years, with the exception of a sharp decline of local supplies in 2008 and onwards as a consequence of the financial crisis and the need to reduce input costs to remain competitive.

some of the largest cities such as Paris or Milan), maintain their position in 2010. The biggest positive effects are observed in the manufacturing sectors of the Netherlands and Belgium, where their major ports acted as the gateway of Europe opened to the rest of the world and gradually approached the core from the peripheral during this period.

5.2. Output increases because of digitalization.

As highlighted by [Tranos et al. \(2021\)](#), engaging with the digital economy has become increasingly crucial in recent decades, as is evidenced by the EU's recognition of it as one of the top ten priorities for the 2015-2019 period accompanied by the launch in 2020 of a new agenda to shape Europe's digital future⁴³. This study also shed light on how the positive productivity growth originated from the adoption of digitalization and digital technologies in a portion of sectors which has diffused among sectors and regions, thereby exerting a long-lasting effect on regional productivity levels.

Based on the results presented by [Gal et al. \(2019\)](#) in their study assessing the impact of the adoption of digital technologies on firm productivity by different activities, we simulate the spatial and sectoral spillover effects of a 10% increase in the rate of adoption of new technologies. This increase in the engagement of digital technologies would be translated into a 0.6% increase in productivity for the Industry (BCDE) sectors and a 0.3% increase for the Market Services (GHIJ) sectors, following [Gal et al. \(2019\)](#) results.

As expected, [Figure 12](#) illustrates how the Industry (BCDE) sectors and the Market Services (GHIJ) sectors experience the most evident effects from this positive shock. However, it is also interesting to highlight how the other sectors exhibit positive impacts too. This suggests the existence of indirect effects beyond the initial direct impacts on those sectors, implying the presence of positive sectoral spillover effects playing a role in explaining changes in productivity.

[Insert Figure 12 here]

Additionally, it is also noticeable that spatial and sectoral heterogeneity is present in these results. On the one hand, while all the values are found to be positive, greater impacts are observed for the remaining tradable sectors, particularly Agriculture (A). Non-market services (OU), on the other hand, due to its lower involvement in trade networks, is less vulnerable to negative shocks but, at the same time, fails to obtain as many benefits from positive shocks compared to other sectors. Moreover, [Figure 12](#) shows the presence of feedback effects in both Industry (BCDE) and Market Services (GHIJ) since most of the regions have larger values compared to the initial increase.

Observing the spatial patterns obtained, we can see that Agriculture (A) and Non-market services (OU) exhibit a homogeneous effect in both cases. However, differences appear for the two sectors initially impacted, especially in the Construction sector (F) and, marginally, in the Real Estate, Financial and other activities (KLMN). Regions at the core of the trade network (e.g., German and Austrian regions) and other areas where Industry and Construction are closely interlinked (such as Southern Spain and Portugal), present effects in construction exceeding 0.2%. When focusing on the two sectors initially shocked, a similar pattern to the one described earlier appears. The regions benefiting most from the positive shock are German regions and those closer to the core, consistently showing higher feedback effects compared to peripheral regions in Spain, Sweden, Italy or France.

Among other policy implications of these results, these findings suggest that policies oriented towards boosting digitalization in Europe (in a symmetric way) may have some unintended consequences in the form of increasing interregional inequalities. The second implication is that the main policy efforts on digitalization should be primarily focused on the peripheral regions since the regions at the center will

⁴³ https://commission.europa.eu/strategy-and-policy/priorities-2019-2024/europe-fit-digital-age_en.

always benefit indirectly via spillover effects, avoiding also the abovementioned unintended consequence of increasing territorial imbalances.

5.3. Output decreases due to the financial crisis.

The 2008 financial crisis had a huge impact on European regional production, however the severity of the impact varied across regions and countries. Since the outbreak of the crisis, many studies have analyzed these spatial imbalances through the concept of regional economic resilience (Martin et al. 2016). Among the determinants of that regional resilience, trade proximity, sectoral embeddedness and interindustry links have been identified as factors explaining the propagation of negative shocks (Kitsos et al., 2023). Even though the financial crisis ended up being a systemic shock, some sectors proved more affected than others at the beginning. One of those sectors was, without any doubt, the Real Estate, Financial & Business Services sector (KLMN).

In this simulation we start by showing the regional and sectoral results of a country specific GDP contraction between 2008 and 2009 in this KLMN sector, together with a spatial asymmetric shock. In particular, we simulate the effects of the average national decline of the sector during the initial year of the crisis: -1.29% for Austrian regions, -1.44% for Belgian regions, -4.66% for German regions, -1.24% for Spanish regions, -1.98% for French regions, -2.16% for Italian regions, -2.67% for Dutch regions, -0.05% for Portuguese regions, and -12.33% for Swedish regions.

As can be seen in Figure 13, the spatial distribution of this negative shock highlights its *asymmetric* nature, with a more pronounced effect on Northern countries, especially Sweden (always displaying a clearer color, as expected). The declines surpassed 1% for all regions except Portugal. If we take a closer look, we observe that some regions are more negatively affected than others within each country due to their interregional and intersectoral linkages. That is the case of some urban and dense areas such as the Île-de-France region (for the Market Services sector – GHIJ) and the Lombardian region in Italy (for the Industry sector – BCDE). Also, bordering regions in Southern and Eastern France, in Northern Spain (for the Market Services sector – GHIJ), and in Northern Germany (for the Agriculture sector – A), present a higher negative effect too, due to their intense trade participation with neighboring countries.

[Insert Figure 13 here]

Finally, at the sectoral level, we find that the negative shock in sector KLMN propagates to all the other sectors. However, this propagation is not homogeneous. Observing the Swedish case for example, the shock in sector KLMN clearly affected the Construction sectors (F) and other Non-market services (OU) a little more, but with all sectors (excluding sector A) presenting declines larger than 0.5%. This negative transmission to the rest of the sectors (again apart from Agriculture), repeats for most of the regions analyzed.

In Figure 14, the map shows the results obtained when we simulate a *symmetric* negative shock on the same sector KLMN. In this case, we simulate the impact of the average GDP drop for those countries between 2008 and 2009, i.e. a common contraction for sector KLMN of -2.84%. The interesting point of this simulation is that the shock is now neutral regarding its magnitude and initially, affects all the regions in the same way.

[Insert Figure 14 here]

In this case, it is easier to see how the other sectors are contaminated by the bursting of the bubble in real estate and financial services through sectoral interconnections. As we hinted in Figure 13, Figure 14 demonstrates the heterogeneous effects across sectors. Without any doubt, Construction (F) and the rest of the Services sectors (GHIJ and OU), display the most negative impacts in comparison with Industry (BCDE) and Agriculture (A), in general. This finding highlights the effect of local interconnections between these sectors and KLMN. In other words, the real estate industry has more impact on local non-tradable sectors, while the more tradable sectors show more resilience to counteract local risk. Even though these

sectors are conventionally considered as non-tradable (Jensen et al., 2005), a negative shock in an interconnected sector will lead to a greater impact on those sectors that provide service to local residents.

This sectoral result holds for most countries, but we can also observe different geographic patterns. In particular, the regions at the center of the trade network seem to be more fragile in terms of the systematic shock, but the geographical heterogeneity seems to be less than the heterogeneity between sectors. In contrast for all sectors, the Spanish and Italian regions suffered a lower negative impact, especially for the Construction (F) and Market services (GHII) sectors.

5.4. *The downturn of the Construction sector in Europe.*

Finally, in order to complement the simulations showed in this section regarding the financial crisis, we perform a last simulation but for the Construction sector (F), which acts as the mainstay industry in almost each region. We have shown in the previous two simulations the clear and strong links between the financial sector, real estate activities, and the construction sector. In this case we simulate the effect of the crisis but starting from the fall in the construction sector between 2008 and 2010 to see how this sector transmitted negative spillovers. Specifically, we simulate a country specific GDP change of -6.97% for Austrian regions, +0.13% for Belgian regions, +2.2% for German regions, -11.80% for Spanish regions, -4.26% for French regions, -6.02% for Italian regions, -8.02% for Dutch regions, -9.14% for Portuguese regions, and -2.83% for Swedish regions.

In Figure 15 we observe how, except for the case of the German regions, the rest of the sectors suffered a negative effect from this shock (between 0 and -0.5%). Spain was visibly the country with the larger decrease in the Construction sector (F) in this period. The results reveal also that this sector has propagated its negative effect to other sectors but especially the KLMN, producing a decrease in this sector of more than 0.5% in several regions. To the contrary, the German case proves very interesting. Germany on average did not suffer any direct negative shock in Construction (F) and consequently most of the sectors did not face a contraction of their GDP. Moreover we observe the importance of this result for German Industry (BCDE) in terms of trade and the indirect effects channeled via commercial networks. In this case, the industry sector had a slight negative impact (lower than 0.5%) due to the fact that the rest of the commercial partners considered (except for Belgium) are seeing their GDPs falling and as a consequence demanding less imports from Germany (offsetting the positive effect of domestic Construction). This result stresses how complex the network of economic dependencies is and how important its role was during the financial crisis.

[Insert Figure 15 here]

5.5. *The Russia-Ukraine war economic consequences*

To approximate some of the economic consequences of the Russia-Ukraine war, we focused our analysis on two simulations: (a) the decrease in the primary sector's TFP for the European regions considered, due to the increase in the price of wheat and other cereals, and (b) the decrease in the industry sector's TFP for the European regions considered, due to the drop in Russian imports.

According to the World Bank⁴⁴, Ukraine and Russia together represent approximately one fourth of total global wheat exports, but they also have a significant participation in the production of other cereals. The price of wheat experienced an increase of 40% in the first months after the beginning of the war, and following Andreyeva et al. (2010), that estimates the demand elasticity to cereal prices at -0.60, we can project an initial decrease in consumption of 24%. Later, based on the information from the Household Budget Survey by Eurostat, we calculate the share of bread and cereal consumption over the total food consumption by countries. Finally, we also calculate the share of primary products consumption over the

⁴⁴ Ruta, Michele; World Bank. *The Impact of the War in Ukraine on Global Trade and Investment (English)*. Equitable Growth, Finance and Institutions Insight Washington, D.C.: World Bank Group.

total output of the primary sector by country using information from WIOD. This allows us to approximate the initial negative shock to the output of the primary sector for our simulation.

Figure 16 shows that the main negative effects appear, as expected, in the sector where the shock is initiated (sector A), and that the potential spillover effects to other sectors are quite limited. The same pattern can be observed when analyzing the results by region. The effect is quite heterogeneous across Europe, with larger decreases in countries experiencing a higher direct negative impact and slightly more negative effects in the regions linked to them.

[Insert Figure 16 here]

For the second simulation, we use information from Eurostat on the most important products imported from Russia and the change in imports between 2022 and 2023. By product category, the most significant imports are those related to the industrial sector (BCDE sector), which present a decline of -74%. Next, using data from WIOD, we calculate the share of BCDE imports from Russia as a proportion of total BCDE imports for each country. Finally, using information contained in WIOD again, we estimate the share of total BCDE imports over total BCDE output. In this second case, we obtain an estimate of the initial negative shock to the output of the BCDE sector by country.

As can be seen in Figure 17, regions closer to the Russian border experience larger initial and indirect negative effects, with trade (as captured by our W matrix) decreasing with distance. In that sense, the most negative effects are found for regions in Sweden, Austria and Germany, although other European regions considered are also impacted. Moreover, clear differences in the propagation of negative effects across sectors can be observed. Services sectors such as Non-Market Services (OU) and Real Estate, Finance and Business Services (KLMN) are substantially less affected due to their lower engagement in trade and, therefore, they are less exposed to spillover effects. However, sectors more closely connected to the Industry Sector, such as Construction (F), Market Services (GHII), and especially Agriculture (A) are significantly more impacted.

[Insert Figure 17 here]

Agriculture (A) production is highly affected by the negative shocks starting in the Industry sector, with effects reaching regions in France and even Spain, which are otherwise hardly affected in terms of their other sectors. Similar to the results found in previous simulations, shocks in the Industry sector propagate to other sectors with greater intensity compared to shocks originated in other sectors. But also, regions at the center of trade network suffer the effect twice as hard as compared to other regions in this simulation, since they are affected both directly by the reduction in imports and indirectly by the amplified effect via spillovers due to their central position in the trade system.

5.6 Discussion

As stated in Subsection 4.4., our spatial production models are in general underestimating the TFP growth of the European regions. We have consciously left the discussion of this issue for this subsection because of the important implications it may have on the measurement of TFP. Well-known organizations, such as the World Bank, often compute TFP growth *à la* Solow, i.e. using a growth accounting approach.⁴⁵ We wonder whether their TFP measures are still overestimating the real technical progress because they have not been adjusted to control for inter-regional and inter-sectoral spillovers via the commercial networks. As national economies are less open to trade than regions' economies, one might argue that we could overlook this issue at country level, but not in a study of highly interconnected regions, as is the case of the European Union.

⁴⁵ It is germane to mention here that the World Bank uses a human capital-adjusted productivity index to control for the contribution of human capital to country's output.

Table 5 provides a country-level comparison of TFP growth rates using different datasets and empirical estimators. All are annual rates of growth in percentages. The first two columns show the average TFP growth rates provided by the WB and PWT for each country over the period 1995-2014. The TFP growth rates depicted in the next three columns have been computed using the BDEURS database, but with different estimators. The third column shows the country-level weighted average of TFP growth rates that were computed using simple growth accounting. The fourth column shows the weighted average of the estimated TFP growth rates that are obtained when a CSS model is used to estimate our production functions. Notice that, like the previous TFP estimations, this model also ignores the existence of inter-regional and inter-sectoral spillovers across the European regions. The last column in this table shows the weighted average of the estimated TFP growth rates that are obtained when we estimate a SAR model that does account for spillovers via the commercial networks.

[Insert Table 5 here]

Several comments are in order regarding Table 5. First, despite the notable differences between the PWT and WB rates of growth, they roughly tell the same story for most countries. For instance, these two databases indicate that Sweden (Italy) has experienced the best (worst) TFP performance from 1995 to 2014. They also show that Spain and Portugal have witnessed a deterioration of their productivity levels in this period. In contrast, the TFP level in Austria, France and Netherlands has improved over time, but at moderate rates. So far, the PWT and WB productivity growth rates are to some extent of a similar magnitude. The TFP growth rates for Germany are positive but differ notably using these two databases. Moreover, they provide contradictory productivity patterns for Belgium.

Second, does the BDEURS database allow us to obtain similar results compared to the two previous, and more well-known, databases? The answer to this question is “yes” but only if we use an estimator (approach) that ignores the existence of the commercial linkages among regions and/or sectors, in the same fashion as the WB and PWT do. This is clearly observable in Table 5 if we compare the previously mentioned productivity patterns (first two columns) with those obtained à la Solow using the BDEURS database (third column). As was the case between the WB and PWT databases, the BDEURS rates of growth of TFP do not coincide with the previous ones. However, the new TFP growth rates again relate a similar story except in the cases of Belgium and Germany where the results using the WB, PWT and BDEURS databases are not very conclusive. For instance, while the largest productivity improvements are found in Sweden followed by Netherlands, the steepest drops in productivity are found in Italy followed by Portugal. The TFP level in Austria and France increases again using the BDEURS database, but at larger rates. We also find a decline in the Spanish TFP, but at more moderate rates than before.

Recall that the above three series of TFP growth rates have been obtained using a growth accounting approach. Like the TFP estimations in column three, we use the same database (BDEURS) in column four but change the estimator. Here we use a non-spatial estimator to estimate the region-sector pair TFP growth rates. We obtain similar productivity trends for each country.⁴⁶ This is an expected result because the CSS estimator still ignores the existence of inter-regional and inter-sectoral spillovers across the European regions.

Notice that, once we add spatial effects (i.e., if we use a SAR specification), the rates fall dramatically except for Italy. If our spatial approach is right, this means that the accounting approach tends to overestimate the true, but unknown, TFP growth or technical progress. Our spatial TFP growth estimate is lower than the previous estimates because it (implicitly) considers the indirect elasticities from the input of neighboring sectors and regions and therefore obtains larger input elasticities when removing the output contribution of capital and labor. This contrasts with a traditional accounting approach or an econometric model that ignores the spatial spillovers across regions and sectors. The larger (total) elasticities found in

⁴⁶ The same conclusion is drawn if we compare Figure 4 with a figure that maps the estimated total TFP growth using a non-spatial model (see Appendix N).

our application using a spatial model simply reflect the fact that the European regions and sectors are closely interconnected via their commercial networks and that a change in the input usage of one region/sector launches inter-regional and inter-sectoral feedback effects that make inputs more productive. In other words, there is more room for productivity improvements if we use a non-spatial approach because this approach does not consider the contribution of neighboring industries' factor input via the commercial networks.

In summary, the performed comparison of TFP growth rates using the same database (BDEURS) allows us to illustrate that we can obtain similar TFP patterns when the two empirical approaches (growth accounting and CSS) used to compute the individual TFP growth rates suffer from the same problem: lack of control of economic effects from other regions and sectors.

6. Conclusions

This paper combines the information of two different databases, BD-EURS and EUREGIO, to examine the role of the trade network and spatial spillovers (at the same time), in explaining the differences in regional TFP for Europe. As far we are aware, this is the first attempt to consider inter-regional links and the position of regions within the commercial network when measuring European regional and sectoral TFP growth. In our analysis, we estimate a neoclassical output per worker growth model with spatial externalities in knowledge. Our empirical growth model is inspired by [Liu et al. \(2022a, b\)](#), [Liu and Sickles \(2023\)](#), and [Han and Sickles \(2024\)](#). While these authors used country-level data, our paper is the first attempt to estimate the proposed production model for a large set of (European) regions that are highly linked via the commercial network.

Our application with regional and sectoral data has proved the flexibility of the proposed specification as it has been able to capture most of regional and sectoral heterogeneity. Using the estimated parameters, we performed several simulations (symmetric and asymmetric shocks), to visualize better how spillovers and commercial networks shape European productivity. Generally speaking, our counterfactual analyses show that both spillovers and commercial networks matter when explaining European productivity.

In fact, these analyses demonstrate how more traditional approaches that overlook these indirect effects tend to underestimate the true impact of both positive and negative shocks on regional productivity growth. We observe a decline in European productivity during the period analyzed, but with some regional and sectoral differences. Across sectors, most present a negative productivity growth, except for Industry. However, without taking into account the offered and received effects, we would be neglecting the attenuating effect that the Industry sector, via knowledge spillovers, would have. Additionally, the effect propagated from other regions cannot be disregarded. As an example, using the results of fourth simulation, we have seen how a mixed shock (positive for Germany and Belgium and negative for other countries) can even reverse the sign in some cases. German and Belgium regions experienced a negative impact in Industry sectors due to the negative effects coming from other regions. Such results would not be captured by a model that does not consider both sectoral and spatial spillovers acting at the same time.

Like [Gude et al. \(2018\)](#), our findings would be valuable for policymakers as they could serve as the basis for building a straightforward categorization of regions based on their presence in trade networks. This could identify regions that are more integrated into value chains, therefore offering and receiving greater impacts from the rest of the regions, as well as regions that are more isolated (with low indirect effects). In this way, policymakers can optimize the allocation of European structural and development funds and design more impactful policies. The analyses presented allow for distinguishing between regions that could benefit from targeted place-based direct policies (such as the Industry sector in certain peripheral and especially in Italian regions) or suffer from some specific adverse shocks (such as the disruption of the shipping channel in the Red Sea due to political conflict), and regions that may not need those direct

policies. Alternatively, those regions not requiring direct policies (as could be the case of Industry in Germany and most core regions, as well as some Spanish regions or those regions unexposed to direct shocks but suffering some recession due to the contagion effect), would instead perhaps benefit from broader industrial policies affecting specific sectors.

Finally, the performed country-level comparison of TFP growth rates suggests that, regardless of the approach used to estimate individual TFP growth rates, we obtain similar TFP patterns if we do consider that all economies are interconnected through the commercial network. There is abundant empirical and theoretical literature suggesting that the global value chains and the trade of intermediate inputs linkages do matter when explaining the economic and productivity performance of national production units (see e.g. [Liu and Sickles, 2021](#); and [Caliendo et al., 2018](#)). Our paper is not an exception. Moreover, as regions are more open to trade than countries, our paper clearly shows that the growth accounting framework needs to be changed to allow for these externalities. In this sense, most institutions providing TFP growth estimates should make an effort to control for a “new” omitted productivity driver in the same fashion that human capital is nowadays controlled using different measures that aims to capture the quality improvements of the labor force.

It is important to highlight here that, as shown by [LeSage \(2008\)](#), we should view the sample of regions as reflecting a long-run equilibrium of an underlying spatiotemporal process, and consequently, we should interpret our feedback effects as reflecting a movement to the next steady state, at least once sufficient time has elapsed for *all* feedback effects to have taken place. In other words, our TFP growth rates are likely ‘aggregating’ feedback effects that have not yet taken place because not yet enough time has elapsed for this to occur. This issue does not invalidate our final conclusion in the previous paragraph but surely calls for a refinement of our spatial econometric model. This we leave for future research.

Data availability

The BD.EURS database is publicly available from <https://www.sepg.pap.hacienda.gob.es/sitios/sepg/es-ES/Presupuestos/DocumentacionEstadisticas/Documentacion/Paginas/BasededatosBDEURS.aspx>. The EUREGIO database is publicly available from <https://data.europa.eu/data/datasets/pbl-euregio-database-2000-2010?locale=en>.

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Compliance with ethical standards

Conflict of interest The authors declare no competing interests.

References

- Acemoglu, D., Akcigit, U., and Kerr, W. (2016). Networks and the Macroeconomy: An Empirical Exploration. *NBER Macroeconomics Annual*, Vol. 30, pp. 273–335
- Acemoglu, D., Autor, D., Dorn, D., Hanson, G.H., and Price, B. (2014). Return of the Solow paradox? IT, productivity, and employment in US manufacturing. *American Economic Review*, 104(5), 394–399.
- Acemoglu, D., Carvalho, V.M., Ozdaglar, A. and Tahbaz-Salehi, A. (2012) “The Network Origins of Aggregate Fluctuations,” *Econometrica*, 80(5), 1977–2016.
- Álvarez, I. C., Barbero, J. (2016). The public sector and convergence with spatial interdependence: empirical evidence from Spain. *Applied Economics*, 48(24), 2238–2252.
- Alvarez, I. C., Barbero, J., Orea, L., and Rodríguez-Pose, A. (2023). How institutions shape the economic returns of public investment in European regions. *Efficiency Series Paper* 03/2023, Oviedo Efficiency Group, University of Oviedo.
- Álvarez, I. C., Condeço-Melhorado, A.M., Gutierrez, J. and Zofío, J.L. (2016). Integrating Network Analysis with the Production Function Approach to Study the Spillover Effects of Transport Infrastructure. *Regional Studies*, 50(6), 996–1015.
- Andreyeva, T., Long, M. W., & Brownell, K. D. (2010). The impact of food prices on consumption: a systematic review of research on the price elasticity of demand for food. *American journal of public health*, 100(2), 216–222.
- Arbués, P., Baños, J. F., and Mayor, M. (2015). The spatial productivity of transportation infrastructure. *Transportation Research Part A: Policy and Practice*, 75, 166–177.
- Ariu, A. (2016). Crisis-proof services: Why trade in services did not suffer during the 2008–2009 collapse. *Journal of International Economics*, 98, 138–149.
- Arrow, K.J. (1962). The Economic Implications of Learning by Doing. *Review of Economics Studies*, 29(3), 155–173.
- Autor, D., and Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share. *NBER Working Paper* No. 24871, National Bureau of Economic Research (NBER), Cambridge, MA.
- Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2017). Concentrating on the Fall of the Labor Share. *American Economic Review*, 107(5), 180–185.
- Ayouba, K. (2023). Spatial dependence in production frontier models. *Journal of Productivity Analysis*, 60, 21–36 (2023). <https://doi.org/10.1007/s11123-023-00670-7>.
- Baldwin, R., and Venables, A. J. (2013). Spiders and snakes: Offshoring and agglomeration in the global economy. *Journal of International Economics*, 90(2), 245–254.
- Baldwin, R., Freeman, R., and Theodorakopoulos, A. (2023). Deconstructing deglobalization: The future of trade is in intermediate services. *Asian Economic Policy Review*, 19, 18–3.
- Balk, B. M. (2016a). The Dynamics of Productivity Change: A Review of the Bottom-up Approach, in *Productivity and Efficiency Analysis*, edited by Greene, W.H., Khalaf, L., Sickles, R.C., Veall, M. and Voia, M.-C. *Proceedings in Business and Economics* (Springer International Publishing, Switzerland).

- Balk, B. M. (2016b). Aggregate Productivity and Productivity of the Aggregate: Connecting the Bottom-Up and Top-Down Approaches. Paper prepared for the 34th IARIW General Conference Dresden, Germany, August 21-27, 2016.
- Baltagi, B. H., Egger, P. H., and Kesina, M. (2016). Firm-level productivity spillovers in China's chemical industry: A spatial Hausman-Taylor approach. *Journal of Applied Econometrics*, 31(1), 214-248.
- Baqae, D. R., and Farhi, E. (2020). Productivity and misallocation in general equilibrium. *The Quarterly Journal of Economics*, 135(1), 105-163.
- Barbero, J., and Zofío, J. L. (2016). The multiregional core-periphery model: The role of the spatial topology. *Networks and Spatial Economics*, 16, 469-496.
- Barca, F. (2009). An Agenda for a Reformed Cohesion Policy-Independent Report. European Commission, Brussels.
- Beugelsdijk, S., Klasing, M.J. and Milionis, P. (2018). Regional economic development in Europe: the role of total factor productivity. *Regional Studies*, 52:4, 461-476.
- Bigio, S., and La'O, J. (2020). Distortions in Production Networks. *The Quarterly Journal of Economics*, 135 (4), 2187-253.
- Bonadio, B., Huo, Z., Levchenko, A.A. and Pandalai-Nayar, N. (2021). Global supply chains in the pandemic. *Journal of International Economics*, 133, 103534.
- Brock, W.A., and Durlauf, S.N. (2001). Discrete choice with social interactions. *The Review of Economic Studies*, 68(2), 235-260.
- Čadil, J., Petkovová, L., and Blatná, D. (2014). Human capital, economic structure and growth. *Procedia Economics and Finance*, 12, 85-92.
- Caliendo, L., Parro, F., Rossi-Hansberg, E., and Sarte, P. D. (2018). The impact of regional and sectoral productivity changes on the US economy. *The Review of economic studies*, 85(4), 2042-2096.
- Cantos, P., Gumbau-Albert, M. and Maudos, J. (2005). Transport infrastructures, spillover effects and regional growth: evidence of the Spanish case. *Transport Reviews*, 25, 25-50.
- Capello, R. and Cerisola, S. (2023). Regional reindustrialization patterns and productivity growth in Europe. *Regional Studies*, 57:1, 1-12.
- Carvalho, V M. and Tahbaz-Salehi, A. (2019). Production Networks: A Primer. *Annual Review of Economics*, Vol. 11, No. 1, pp. 635–63.
- Clark, T.S., and Linzer, D.A. (2014). Should I Use Fixed or Random Effects? *Political Science Research and Methods*, 3, 399 - 408.
- Coe, D.T., and Helpman, E. (1995). International R&D Spillovers. *European Economic Review*, 39 (5), 859-87.
- Cornwell, C., Schmidt, P., and Sickles, R.C. (1990). Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics*, 46(1-2), 185–200.
- De Avillez, R. (2012). Sectoral contributions to labor productivity growth in Canada: does the choice of decomposition formula matter?. *International Productivity Monitor*, 24, Fall, 97–117.
- Delgado, M. S., Henderson, D. J., and Parmeter, C. F. (2014). Does education matter for economic growth?. *Oxford Bulletin of Economics and Statistics*, 76(3), 334-359.
- Diemer, A., Iammarino, S., Rodríguez-Pose, A., and Storper, M. (2022). The regional development trap in Europe. *Economic Geography*, 98(5), 487-509.

- Diewert, W. E., and Wales, T. J. (1992). Quadratic spline models for producer's supply and demand functions. *International Economic Review*, 33(3):705-722.
- Ertur, C. and W. Koch (2011). A Contribution to the Theory and Empirics of Schumpeterian Growth with Worldwide Interactions. *Journal of Economic Growth*, Vol. 16, No. 3, pp. 215–255.
- Escribá-Pérez, J., Gómez-Tello, A., Murgui-García, M. J., and Sanchís-Llopis, M. T. (2019). BD. EURS (NACE Rev. 2) database: New estimations. *Documento de Trabajo D-2019-01*.
- Fageda X. (2014). What hurts the dominant airlines at hub airports? *Transportation Research Part E*, 70(1):177-189.
- Färe, R., Grosskopf, S., Norris, M., and Zhang, Z. (1994). Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review*, 66-83.
- Fingleton, B., Garretsen, H., and Martin, R. (2012). Recessionary shocks and regional employment: evidence on the resilience of UK regions. *Journal of Regional Science*, 52(1), 109-133.
- Foray, D., McCann, P., and Ortega-Argilés, R. (2015). Smart specialization and European regional development policy. *Oxford Handbook of Local Competitiveness*, 458-480.
- Gadea-Rivas, M. D., Gómez-Loscos, A., and Leiva-Leon, D. (2019). Increasing linkages among European regions. The role of sectoral composition. *Economic Modelling*, 80, 222-243.
- Gal, P., Nicoletti, G., Renault, T., Sorbe, S., and Timiliotis, C. (2019). Digitalisation and productivity: In search of the holy grail—Firm-level empirical evidence from EU countries. *International Productivity Monitor*, 37(Fall), 39-71.
- Glass, A. J., Kenjegalieva, K., and Sickles, R.C. (2014). Estimating efficiency spillovers with state level evidence for manufacturing in the US. *Economic Letters*, 123(2), 154–159.
- Glass, A. J., Kenjegalieva, K., and Sickles, R.C. (2016). Returns to Scale and Curvature in the Presence of Spillovers: Evidence from European Countries. *Oxford Economic Papers-New Series*, 68 (1), 40-63.
- Gómez-Loscos, A., Gadea, MD., and Bandres, E. (2020). Business cycle patterns in European regions. *Empirical Economics*, 59, 2639-2661.
- Gómez-Tello, A., Murgui-García, M. J., and Sanchis-Llopis, M. T. (2020). Exploring the recent upsurge in productivity disparities among European regions. *Growth and Change*, 51(4), 1491-1516.
- Greene, W. H. (1980). Maximum likelihood estimation of econometric frontier functions. *Journal of Econometrics*, 13(1), 27-56.
- Gude, A., Álvarez, I., and Orea, L. (2018). Heterogeneous spillovers among Spanish provinces: a generalized spatial stochastic frontier model. *Journal of Productivity Analysis*, 50, 155-173.
- Han, J. (2016). Essays on Treatments of Cross-Section Dependence in Panel Data Models. PhD dissertation. Rice University.
- Han, J. and Sickles, R.C. (2024). Estimation of Industry-level Productivity with Cross-sectional Dependence using Spatial Analysis. *Journal of Productivity Analysis*, forthcoming.
- Ho, C.Y., Wang, W., and Yu, J.H. (2018). International Knowledge Spillover through Trade: A Time-Varying Spatial Panel Data Approach. *Economics Letters*, 162, 30-33, 2018.
- ILO. (2019). *The Global Labour Income Share and Distribution*, Paris: OECD.
- Isard, W. (1951). Interregional and regional input-output analysis: a model of a space-economy. *Review of Economics and Statistics*, 33(4), 318-328.

- Islam, N. (1995). Growth empirics: a panel data approach. *The Quarterly Journal of Economics*, 110(4), 1127-1170.
- Jensen, J. B., Kletzer, L. G., Bernstein, J., and Feenstra, R. C. (2005). Tradable services: Understanding the scope and impact of services offshoring [with comments and discussion]. In *Brookings trade forum* (pp. 75-133). Brookings Institution Press.
- Jorgenson, D. W., Ho, M. S., Samuels, J. D., and Stiroh, K. J. (2007). Industry origins of the American productivity resurgence. *Economic Systems Research*, 19(3), 229-252.
- Kenourgios, D., and Dimitriou, D. (2015). Contagion of the Global Financial Crisis and the real economy: A regional analysis. *Economic Modelling*, 44, 283-293.
- Kitsos, T., Grabner, S. M., and Carrascal-Incera, A. (2023). Industrial embeddedness and regional economic resistance in Europe. *Economic Geography*, 99(3), 227-252.
- LeSage, J. (2008). An Introduction to Spatial Econometrics. *Revue d'économie industrielle*, 123|3e trimestre, Varia, 19-44.
- LeSage, J., and Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.
- Liu and Sickles (2023), "Industry-specific productivity and spillovers through input-output linkages: evidence from Asia-Pacific value chain", *Review of Income and Wealth*, forthcoming.
- Liu, W., Cheng, Q., and Sickles, RC (2022b). Productivity Growth and Spillover across European Industries: A Global Value Chain Perspective Based on EURO KLEMS. *WORLDKLEMS*, No. 22-001.
- Liu, W., R.C. Sickles and Y. Zhao (2022a). Measuring Productivity Growth and Technology Spillovers Through Global Value Chains: Analysis of a US–Sino Decoupling. in A. Chudik, C. Hsiao, and A. Timmermann (Ed.), *Essays in Honor of M. Hashem Pesaran: Prediction and Macro Modeling* (Advances in Econometrics Vol. 43A), Emerald Publishing Limited, pp. 243-267.
- Mankiw, G.N., Romer, D. and Weil, D.N. (1992). A contribution to the empirics of Economic Growth. *The Quarterly Journal of Economics*, 107(2), 407-437.
- Martin, R., Sunley, P., Gardiner, B., and Tyler, P. (2016). How regions react to recessions: Resilience and the role of economic structure. *Regional studies*, 50(4), 561-585.
- McCann, P., and Ortega-Argilés, R. (2016). The early experience of smart specialization implementation in EU cohesion policy. *European Planning Studies*, 24(8), 1407-1427.
- Myrdal, G. (1957). *Economic Theory and under-developed regions*. Duckworth, London.
- Orea, L. (2002). Parametric decomposition of a generalized Malmquist productivity index. *Journal of Productivity Analysis*, 18, 5-22
- Orea, L. and Álvarez, I.C. (2019). A new stochastic frontier model with cross-sectional effects in both noise and inefficiency terms. *Journal of Econometrics*, 213(2), 556–577.
- Orea, L., Álvarez, I. C. and Servén, L. (2024). The structural and productivity effects of infrastructure provision in developed and developing countries, *Essays in Honor of Subal Kumbhakar (Advances in Econometrics)*, (Vol. 46, pp. 265-308). Emerald Group Publishing Limited.
- Parmeter, C. F., and Kumbhakar, S. C. (2014). Efficiency analysis: a primer on recent advances. *Foundations and Trends® in Econometrics*, 7(3–4), 191-385.
- Pereira, A. M., and Andraz, J. M. (2013). On the economic effects of public infrastructure investment: A survey of the international evidence. *Journal of Economic Development*, 38(4), 1-37.
- Piketty, T. (2014). *Capital in the Twenty First Century*, Cambridge: Harvard University Press.

- Plümper, T., and Neumayer, E. (2010). Model specification in the analysis of spatial dependence. *European Journal of Political Research*, 49(3), 418-442.
- Restuccia, D., and Rogerson, R. (2013). Misallocation and productivity. *Review of Economic Dynamics*, 16(1), 1-10.
- Rodríguez-Pose, A. and Ketterer, T. (2020). Institutional Change and the Development of Lagging Regions in Europe. *Regional Studies*, 54(7), 974–986.
- Rodríguez-Pose, A., and Ganau, R. (2022). Institutions and the productivity challenge for European regions. *Journal of Economic Geography*, 22(1), 1-25.
- Rodríguez-Pose, A., Psacharidis, J. and Tselios, V. (2012). Public investment and regional growth and convergence evidence from Greece. *Papers in Regional Science*, 91, 543-568.
- Romer, P.M. (1986). Increasing returns and long-run growth. *Journal of Political Economy*, 94(5), 1002-1037.
- Sickles, R., and Zelenyuk, V. (2019). *Measurement of Productivity and Efficiency: Theory and Practice*. Cambridge: Cambridge University Press.
- Solow, R. M. (1956). A contribution to the theory of economic growth. *The Quarterly Journal of Economics*, 70(1), 65-94.
- Sun, Y., Heinz, F. and Ho, G. (2013), Cross-country linkages in Europe: A Global VAR analysis. *International Monetary Fund*.
- Swan, T. W. (1956). Economic growth and capital accumulation. *Economic record*, 32(2), 334-361.
- Thissen, M., Diodato, D., and Van Oort, F. (2013). European regional trade flows: An update for 2000–2010. *PBL Netherlands Environmental Assessment Agency*, The Hague.
- Thissen, M., Lankhuizen, M., van Oort, F., Los, B., and Diodato, D. (2018). EUREGIO: The construction of a global IO DATABASE with regional detail for Europe for 2000–2010. *Tinbergen Institute Discussion Paper* 2018-084/VI.
- Tiefelsdorf, M., Griffith, D. A. and Boots, B. (1999). A variance-stabilizing coding scheme for spatial link matrices. *Environment and Planning A*, 31, 165–180
- Timmer, M., and Ye., X. (2018). Productivity and Substitution Patterns in Global Value Chains. in E. Grifell-Tatjé, C.A.K. Lovell and R. Sickles (eds.), *The Oxford Handbook of Productivity Analysis*. Oxford University Press, Oxford, NY, Chap. 21, 2018.
- Timmer, M.P., E. Dietzenbacher, B. Los, R. Stehrer and de Vries, G.J. (2015). An illustrated user guide to the World Input-Output Database: The case of global automotive production. *Review of International Economics*, 23(3), 575-605
- Tranos, E., Carrascal-Incera, A., and Willis, G. (2023). Using the Web to Predict Regional Trade Flows: Data Extraction, Modeling, and Validation. *Annals of the American Association of Geographers*, 113(3), 717-739.
- Tranos, E., Kitsos, T., and Ortega-Argilés, R. (2021). Digital economy in the UK: regional productivity effects of early adoption. *Regional Studies*, 55(12), 1924-1938.
- Wang, W. S., and Schmidt, P. (2009). On the distribution of estimated technical efficiency in stochastic frontier models. *Journal of Econometrics*, 148(1), 36-45.
- Weil, D. (2015). Capital, wealth, growth, and inequality in the 21st century. Presentation to the National Economic Research Organizations (NERO) meeting.
- Wooldridge, J. M. (2015). *Introductory Econometrics: A Modern Approach*. Toronto: Nelson Education.

Zelenyuk, V. (2024). Aggregation in efficiency and productivity analysis: a brief review with new insights and justifications for constant returns to scale. *Journal of Productivity Analysis*, 62, 321–334 (2024).

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Tables and Figures of the Main Text

Table 1. Summary statistics. BDEURS dataset.*a) Countries*

Variable	Obs	Mean	Std. Dev.	Min	Max	Variable	Obs	Mean	Std. Dev.	Min	Max
Austria						Netherlands					
VA	1,080	4486.945	4470.412	15.73	22350.57	VA	1,440	7203.45	8453.635	212.04	42946.45
K	1,080	17610.9	24839.71	244.87	181751.3	K	1,440	25557.48	40507.11	139.33	258587.3
L	1,080	72.3297	65.30854	0.941	309.633	L	1,440	116.1445	130.1719	5.301	608.362
Belgium						Portugal					
VA	1,320	4513.412	4557.599	0.95	23976.16	VA	600	4914.258	4899.149	197.71	19431.6
K	1,320	15047.31	19346.67	46.27	110331.3	K	600	15554.68	23560.9	155.34	134003.2
L	1,320	64.33664	59.7177	0.1	279.285	L	600	162.5251	141.7229	9.815	577.546
France						Spain					
VA	2,640	12742.11	22643.2	50.71	228349.9	VA	2,040	8563.232	10629.53	96.42	62247.52
K	2,640	48081.42	123147.7	241.67	1550396	K	2,040	31101.69	50825.15	186.16	343684.4
L	2,640	197.4337	281.8097	4.717	1996.907	L	2,040	175.5912	219.0207	4.6	1211.5
Germany						Sweden					
VA	1,920	23032.79	31166.98	2.99	147101.1	VA	960	6321.876	6337.782	90.54	38160.53
K	1,920	84458.49	159891.9	109.15	1140706	K	960	18502.88	24214.28	380.15	182961.4
L	1,920	416.6079	528.8042	0.36	2887.656	L	960	91.48853	91.14492	2.968	399
Italy						All countries					
VA	2,520	11200.32	15175.94	38.29	98959.95	VA	14,520	10588.85	17979.53	0.95	228349.9
K	2,520	40750.76	70211.32	283.29	566754.2	K	14,520	38430.8	90052.88	46.27	1550396
L	2,520	189.6909	234.192	2	1286.4	L	14,520	184.089	286.0405	0.1	2887.656

b) Sectors

Variable	Obs	Mean	Std. Dev.	Min	Max	Variable	Obs	Mean	Std. Dev.	Min	Max
Agriculture						PM Services					
VA	2,420	1040.825	989.2366	0.95	7874.18	VA	2,420	14547.45	19259.78	781.1	170720.9
K	2,420	5365.411	5277.175	46.27	33146.3	K	2,420	24489.97	29509.58	1108.62	266013.4
L	2,420	39.04317	45.52501	0.1	343.634	L	2,420	293.8938	361.1334	15.936	2407.766
Construction						RSFB Services					
VA	2,420	3981.149	4258.962	274.95	27036.53	VA	2,420	16701.02	25925.11	574.44	228349.9
K	2,420	3480.164	4730.428	139.33	41853.75	K	2,420	128641.6	183657.9	3478.32	1550396
L	2,420	78.60812	85.2063	5.2	535.98	L	2,420	166.0576	231.7526	4.952	1665.117
Industry						NM Services					
VA	2,420	12709.91	19578.77	228.48	139589.9	VA	2,420	14552.72	16929.29	856.58	115384
K	2,420	32561.81	41206.72	667.22	269309.5	K	2,420	36045.8	40408.76	2383.27	284014.4
L	2,420	190.599	282.8157	4.989	2106.467	L	2,420	336.3319	387.0982	15.725	2887.656

Table 2. RE parameter estimates.

	RE-Hicks neutral				RE-Hicks non-neutral			
	SAR		SDM		SAR		SDM	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
lnk	0.407***	0.007	0.397***	0.008	0.381***	0.008	0.365***	0.009
W·lnk			0.076***	0.019			0.087***	0.022
lnk·t					0.005***	0.000	0.008***	0.001
W·lnk·t							-0.006***	0.001
t	-0.005***	0.001	-0.006***	0.001	-0.032***	0.002	-0.014**	0.006
W·lny	0.406***	0.014	0.386***	0.016	0.417***	0.014	0.398***	0.016
Agriculture	-0.510***	0.051	-0.493***	0.051	-0.526***	0.053	-0.507***	0.052
Industry	0.303***	0.051	0.328***	0.051	0.217***	0.053	0.225***	0.052
Construction	0.523***	0.051	0.521***	0.051	0.652***	0.053	0.676***	0.052
PM Services	0.216***	0.051	0.216***	0.050	0.197***	0.053	0.189***	0.051
RSFB Services	0.000	0.053	0.041	0.054	0.039	0.055	0.111**	0.056
Austria	-0.180**	0.078	-0.173**	0.077	-0.262***	0.081	-0.289***	0.079
Belgium	-0.069	0.075	-0.061	0.074	-0.126	0.077	-0.138*	0.076
Germany	-0.165**	0.070	-0.150**	0.069	-0.184**	0.072	-0.190***	0.071
Spain	-0.148**	0.069	-0.131*	0.069	-0.143**	0.072	-0.138**	0.070
France	-0.044	0.067	-0.039	0.066	-0.071	0.069	-0.085	0.067
Italy	-0.124*	0.067	-0.108	0.066	-0.134*	0.069	-0.133**	0.068
Netherlands	-0.034	0.074	-0.016	0.073	-0.063	0.076	-0.062	0.075
Portugal	-0.253***	0.092	-0.211**	0.092	-0.172*	0.095	-0.124	0.095
intercept	-0.007	0.066	-0.019	0.066	0.287***	0.073	0.079	0.089
sigma	0.007		0.007		0.006		0.006	
R2	0.791		0.716		0.6817		0.748	
LnL	16128.66		16130.755		16295.015		16436.429	

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Table 3. Direct, Indirect, and Overall effects of input factors.*a) RE-Hicks neutral. SAR model.*

	Direct effect	z-value	Indirect effect	z-value	Overall effect	z-value
Capital	0.411	55.029	0.274	16.965	0.685	37.086
Labor	0.589	-	-0.274	-	0.315	-

b) RE-Hicks non-neutral. SAR model.

	Direct effect	z-value	Indirect effect	z-value	Overall effect	z-value
<i>Time-invariant component</i>						
Capital	0.387	48.206	0.268	17.428	0.655	34.470
Labor	0.613	-	-0.268	-	0.345	-
<i>Time-varying component</i>						
Capital	0.005	44.995	0.004	17.183	0.009	32.972
Labor	-0.005	-	-0.004	-	-0.009	-

Note: the time-varying component has to do with the interaction of logged capital-labor ratio with the time trend.

Table 4. Descriptive statistics of the efficiency scores (1995-2014).

Sector	CSS model				
	Obs.	Mean	Std. Dev.	Min	Max
Agriculture	2,420	43.5	15.1	5.2	100
Industry	2,420	33.7	13.2	10.3	100
Construction	2,420	68.2	16.4	22.3	100
PM Services	2,420	70.0	10.6	40.7	100
RSFB Services	2,420	66.4	12.6	36.7	100
NM Services	2,420	68.0	10.0	37.4	100
All sectors	14,520	58.3	19.4	5.2	100
Sector	SAR model				
	Obs.	Mean	Std. Dev.	Min	Max
Agriculture	2,420	45.2	20.1	6.5	100
Industry	2,420	23.6	12.1	6.0	100
Construction	2,420	51.8	17.5	14.3	100
PM Services	2,420	55.2	17.6	20.3	100
RSFB Services	2,420	51.8	18.0	19.1	100
NM Services	2,420	52.2	17.8	16.2	100
All sectors	14,520	46.7	20.4	6.0	100

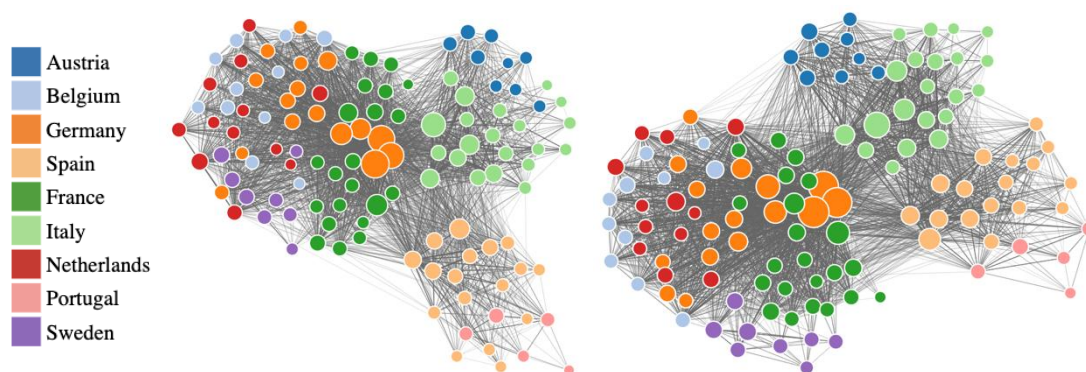
Note: Efficiency scores in percentage.

Table 5. Comparison of TFP growth rates (1995-2014).

Country	WB	PWT	BDEURS ^(a)	Estimated TFP growth	
				Non-spatial ^{(a)(b)}	Spatial ^{(a)(c)}
Austria	0.056	0.145	0.419	0.489	0.184
Belgium	0.235	-0.064	0.151	0.169	-0.377
Germany	0.147	0.361	-0.037	-0.032	-0.436
Spain	-0.631	-0.561	-0.221	-0.299	-0.777
France	0.039	0.121	0.255	0.211	-0.218
Italy	-0.994	-0.906	-0.722	-0.836	-1.141
Netherlands	0.239	0.194	0.484	0.395	-0.121
Portugal	-0.396	-0.446	-0.475	-0.634	-1.448
Sweden	0.993	0.759	0.590	0.163	-0.506

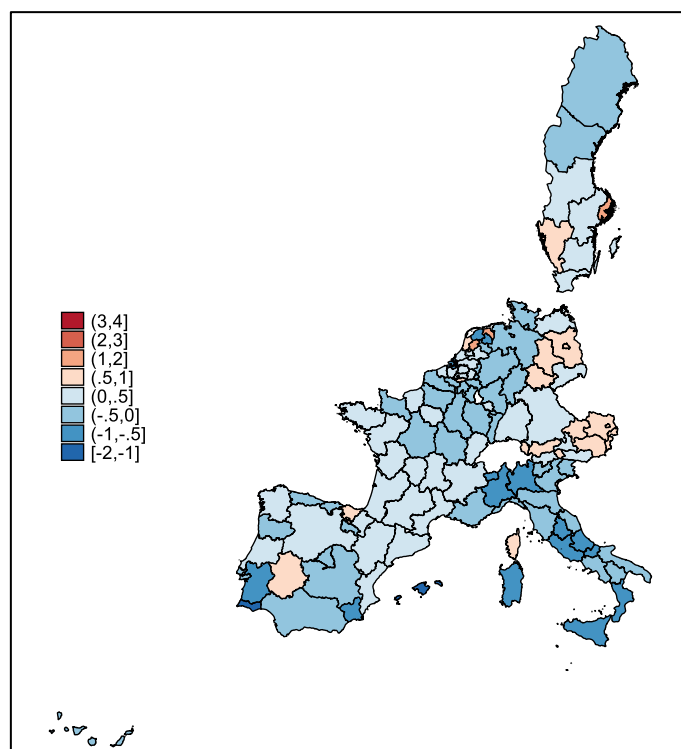
Notes: TFP growth rates in percentage. (a) Weighted average of region-sector's TFP growth rates. (b) Estimates from a CSS Hicks-neutral model. (c) Estimates from a SAR Hicks-neutral model.

Figure 1. Network trade flows between European regions. Industry sector.



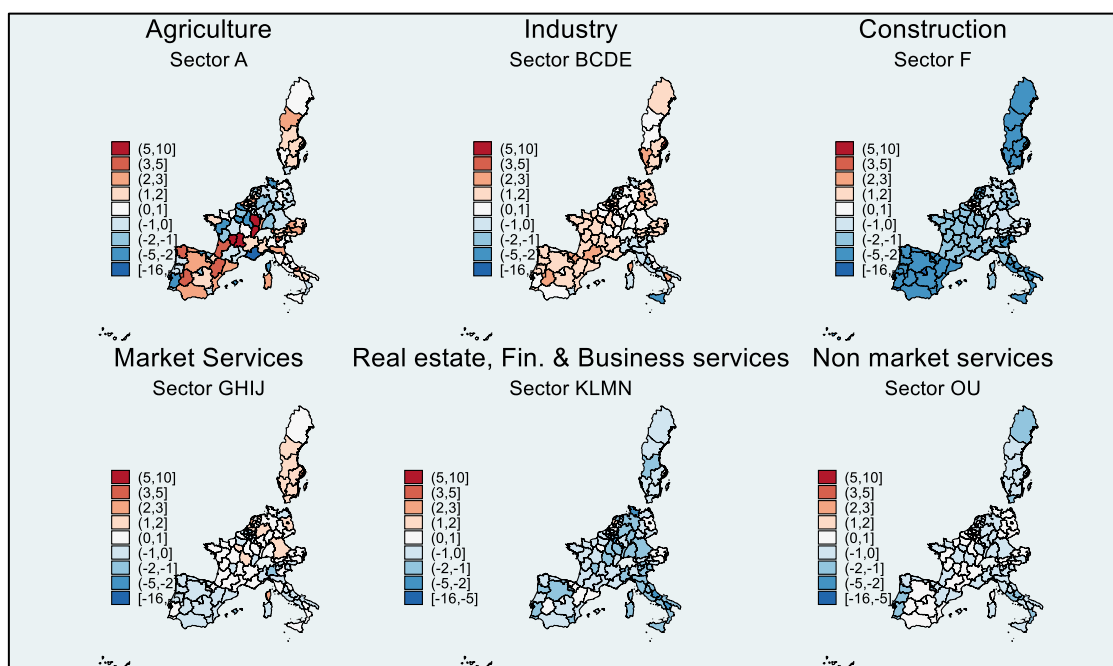
Note: Subsectors included Extractive industries, Manufactures, Energy and Water supply. Data obtained from EUREGIO. Threshold for the link to be included: 20 million Euros. Year 2000 (on the left) and year 2010 (on the right).

Figure 2. Regional growth accounting TFP. 1995-2014.



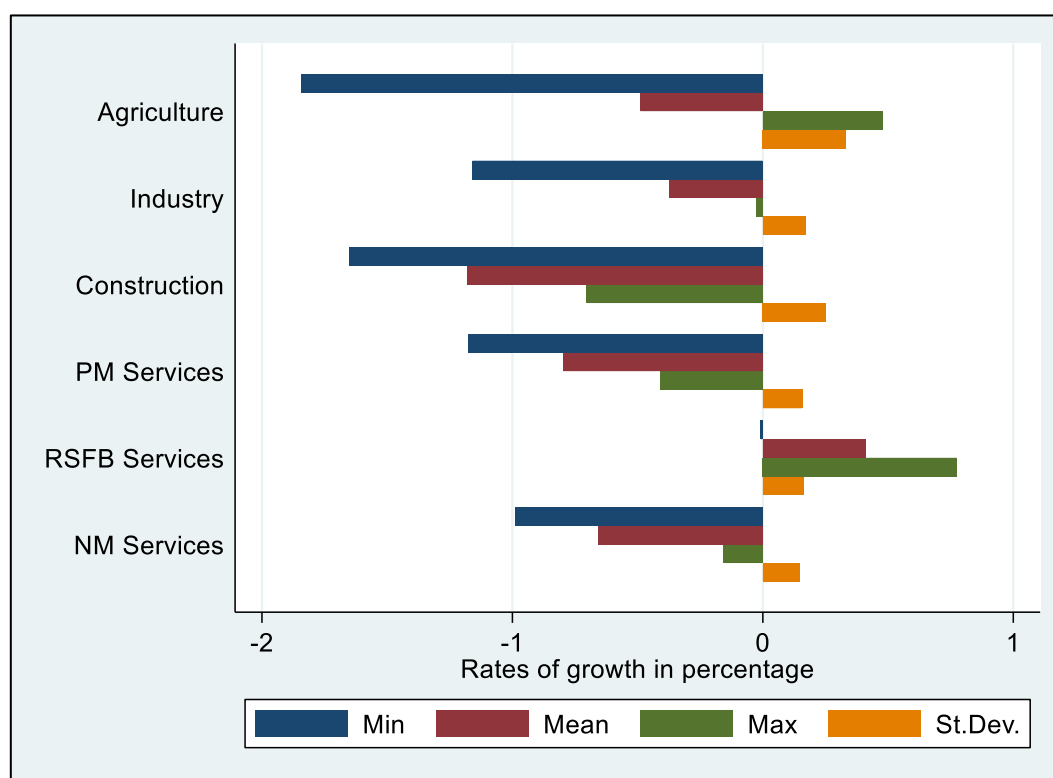
Note: Annual rate of growth in percentage.

Figure 3. Sectoral growth accounting TFP. 1995-2014.



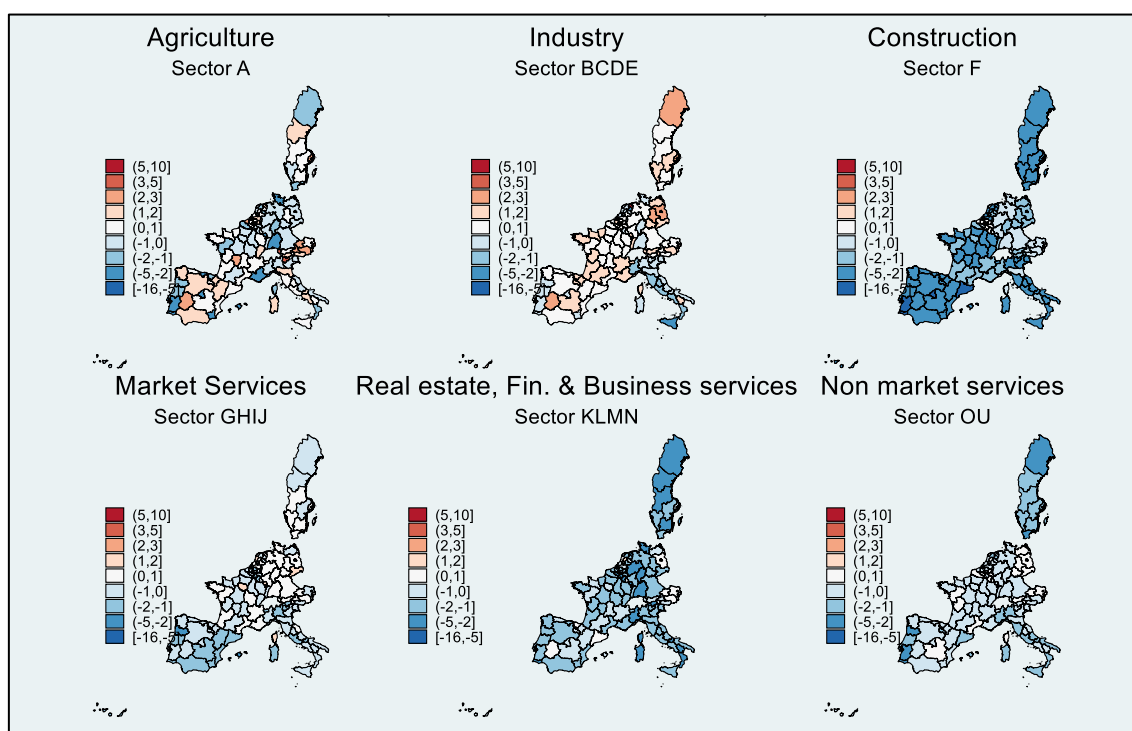
Note: Annual rate of growth in percentage.

Figure 4. Rates of technical change by sector. Non-neutral SAR model.



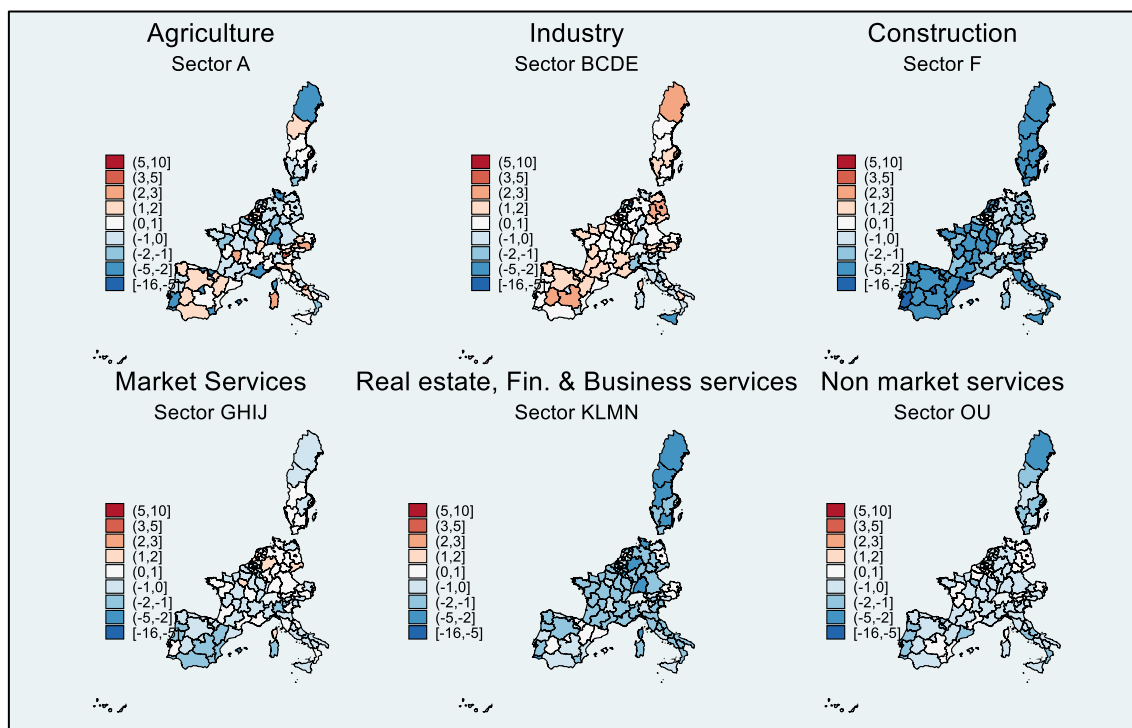
Note: Annual rates of growth.

Figure 5. Estimated total TFP growth from the received direction. 1995-2014.



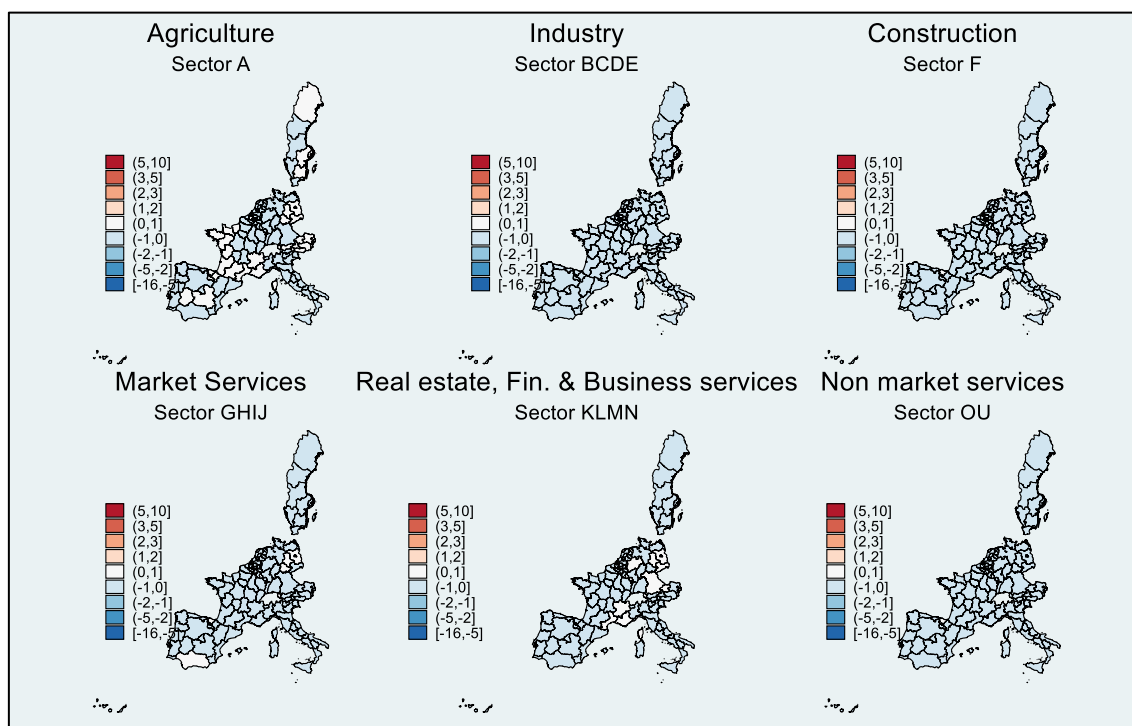
Note: Annual rate of growth in percentage. SAR model estimated using a RE estimator. Hicks neutral specification.

Figure 6. Estimated direct TFP growth. 1995-2014.



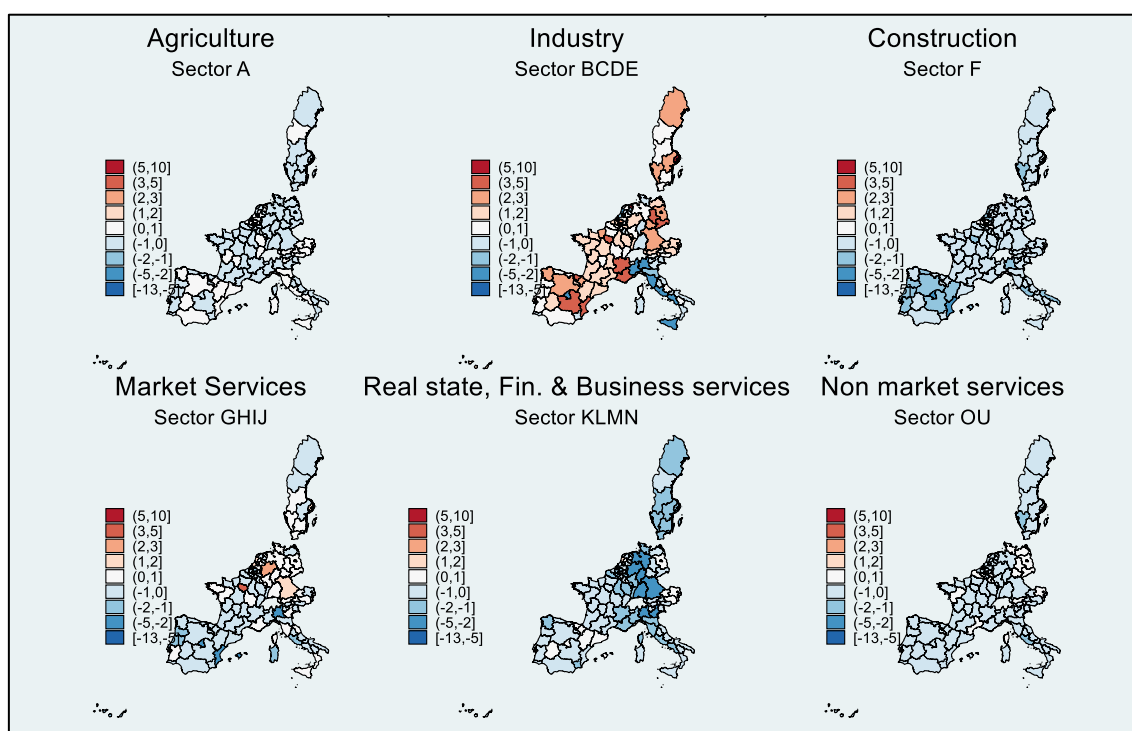
Note: Annual rate of growth in percentage. SAR model estimated using a RE estimator. Hicks neutral specification.

Figure 7. Estimated indirect TFP growth from the received direction. 1995-2014.



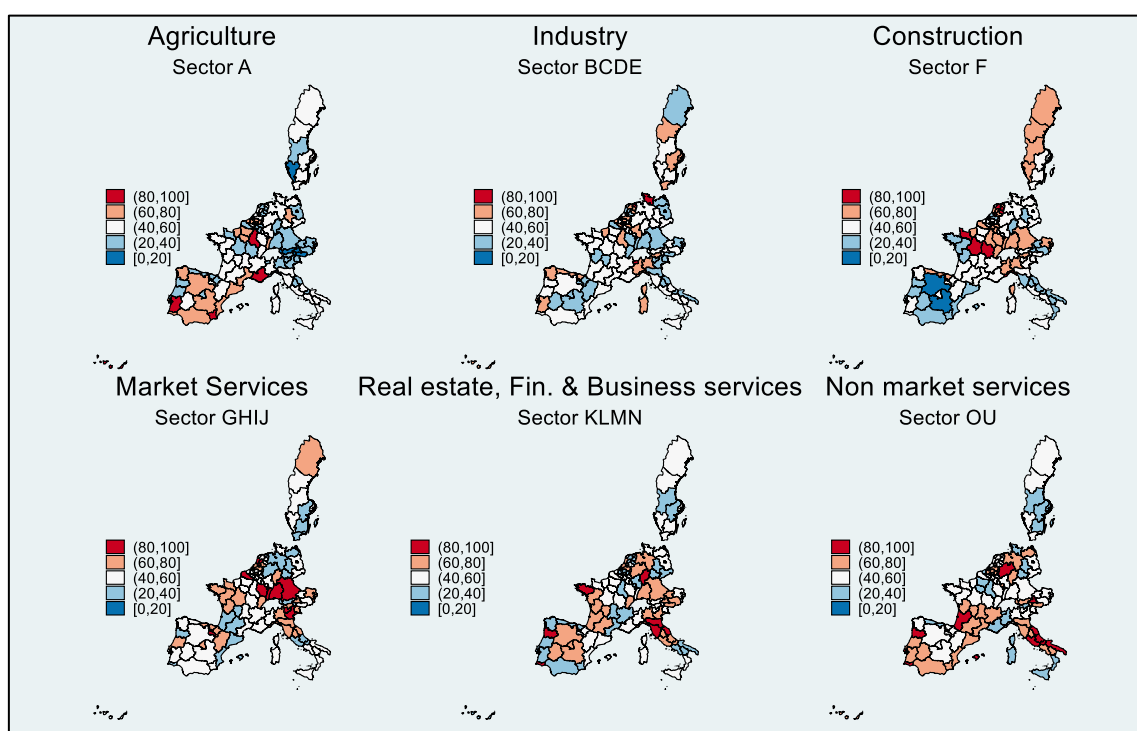
Note: Annual rate of growth in percentage. SAR model estimated using a RE estimator. Hicks neutral specification.

Figure 8. Estimated indirect TFP growth from the offered direction. 1995-2014.



Note: Annual rate of growth in percentage. SAR model estimated using a RE estimator. Hicks neutral specification.

Figure 9. Average efficiency scores (1995-2014). SAR model.



Note: Efficiency scores in percentage using a RE and SAR model with Hicks neutral productivity change.

Figure 10. Robustness Analyses. TFP growth rates. SAR model.

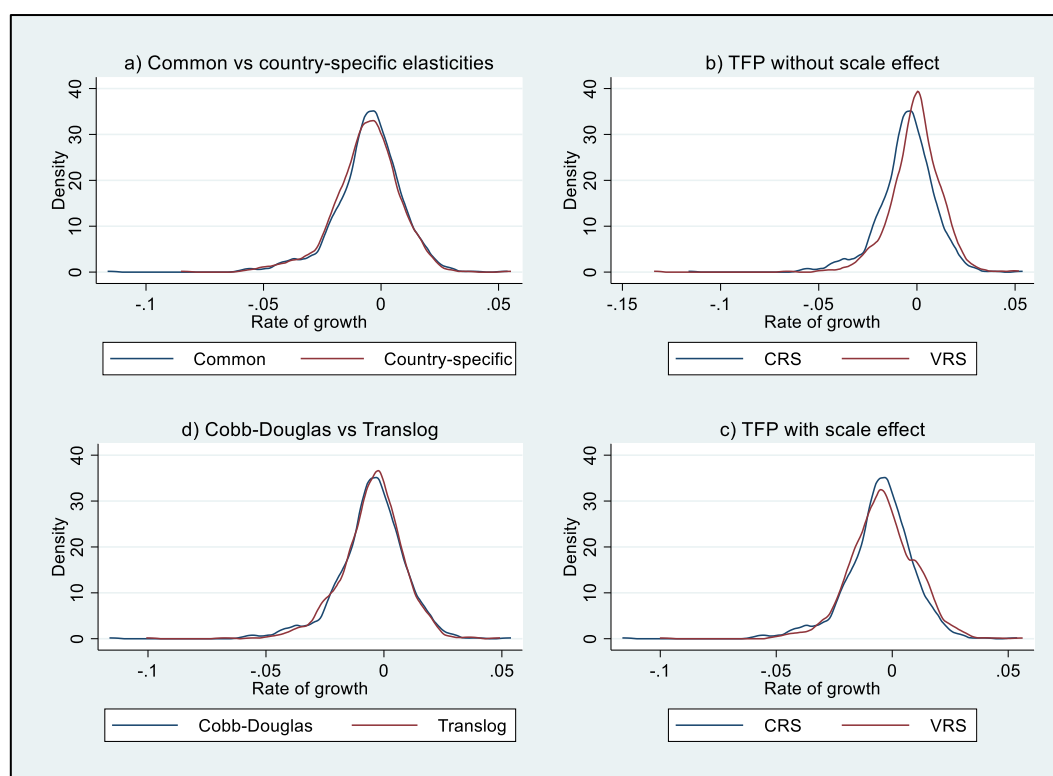


Figure 11. Output increases due to changes in trade network.

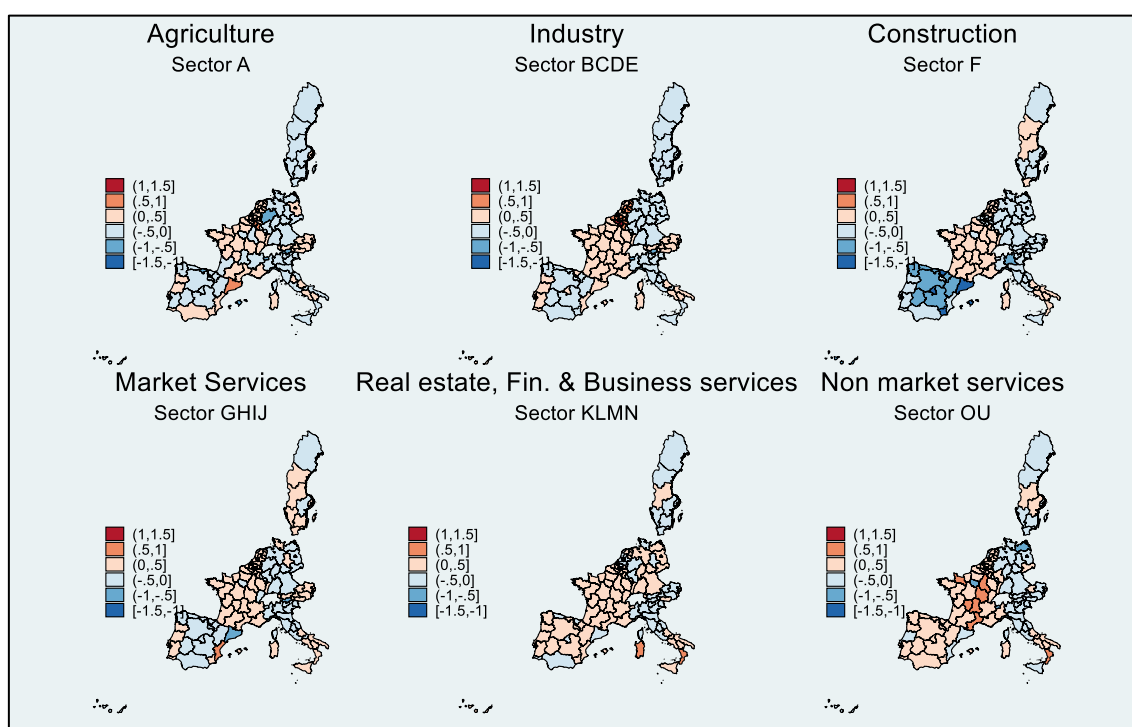


Figure 12. Output increases due to digitalization.

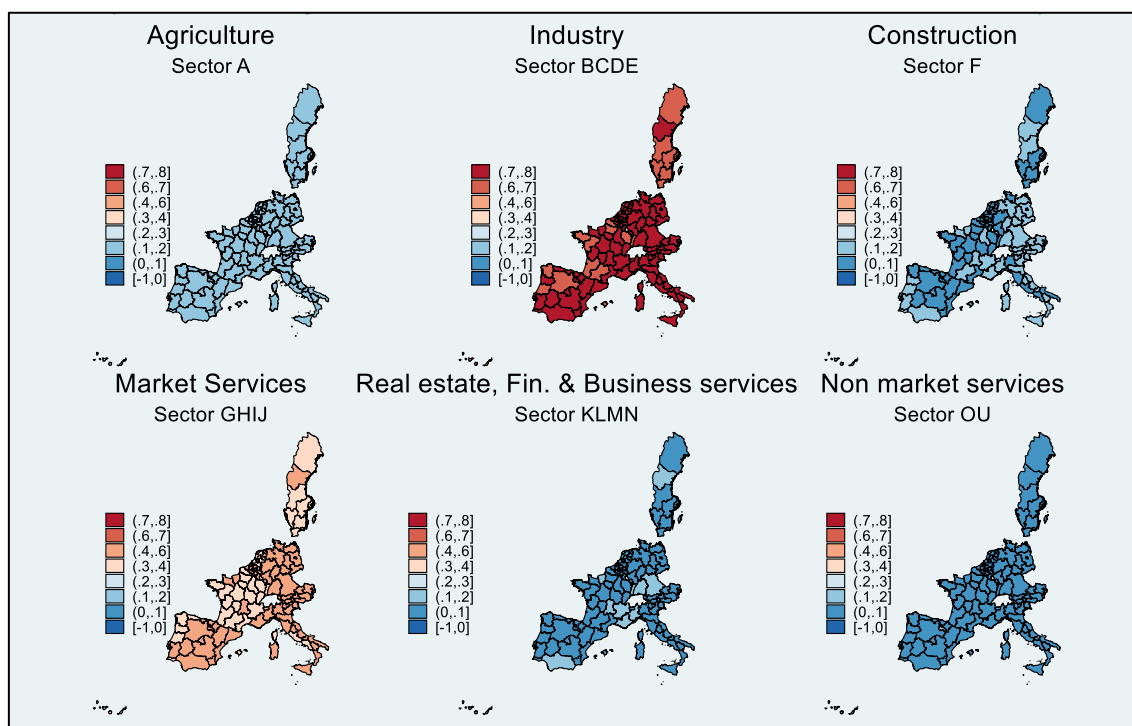


Figure 13. Output effects caused by the financial crisis (asymmetric shocks).

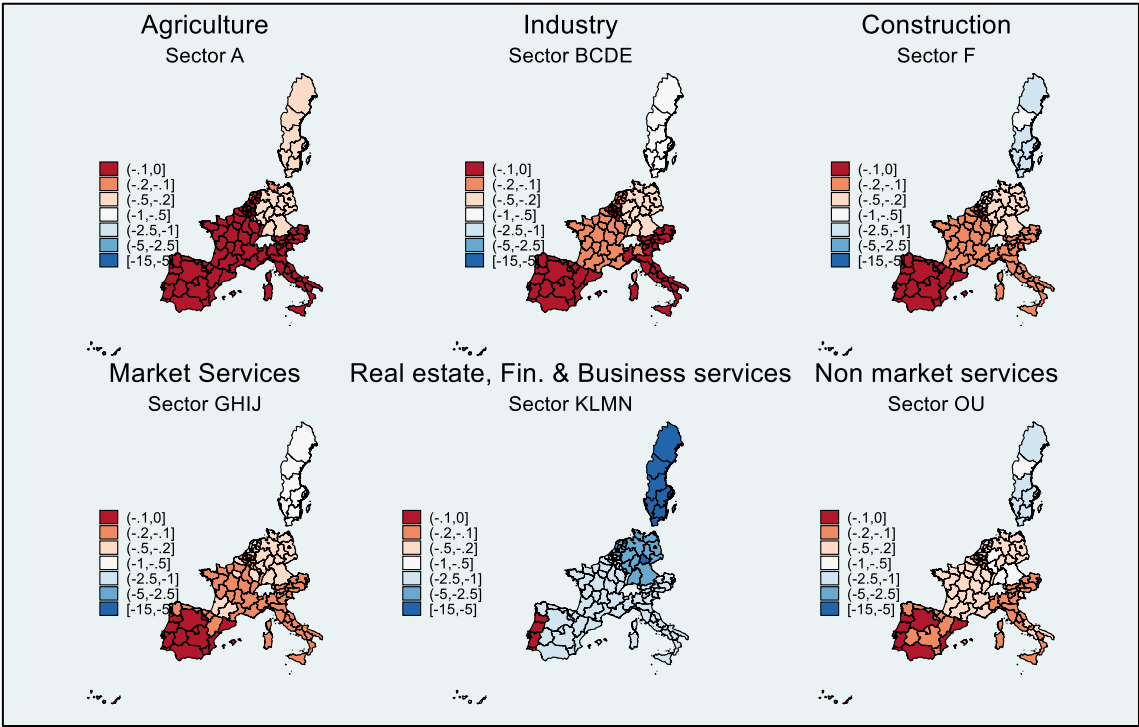


Figure 14. Output effects caused by the financial crisis (symmetric shock).

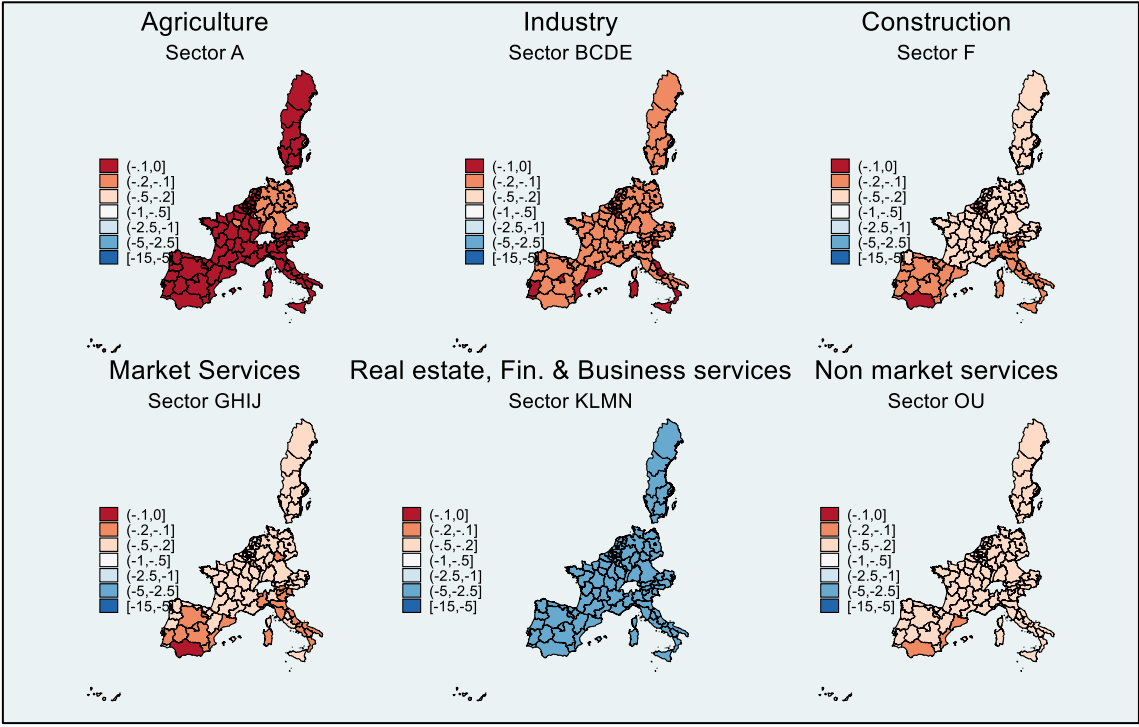


Figure 15. Output effects caused by the collapse of the construction sector.

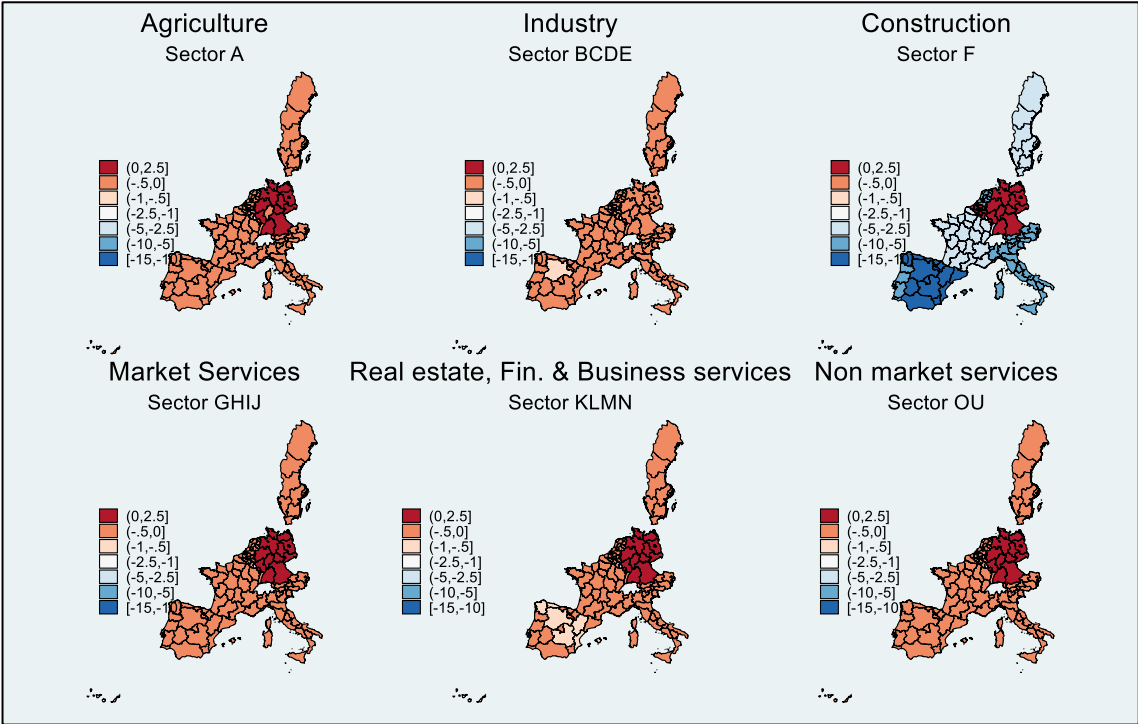


Figure 16. Output reductions due to a decrease in Agriculture caused by a reduction in the consumption of wheat and other cereals.

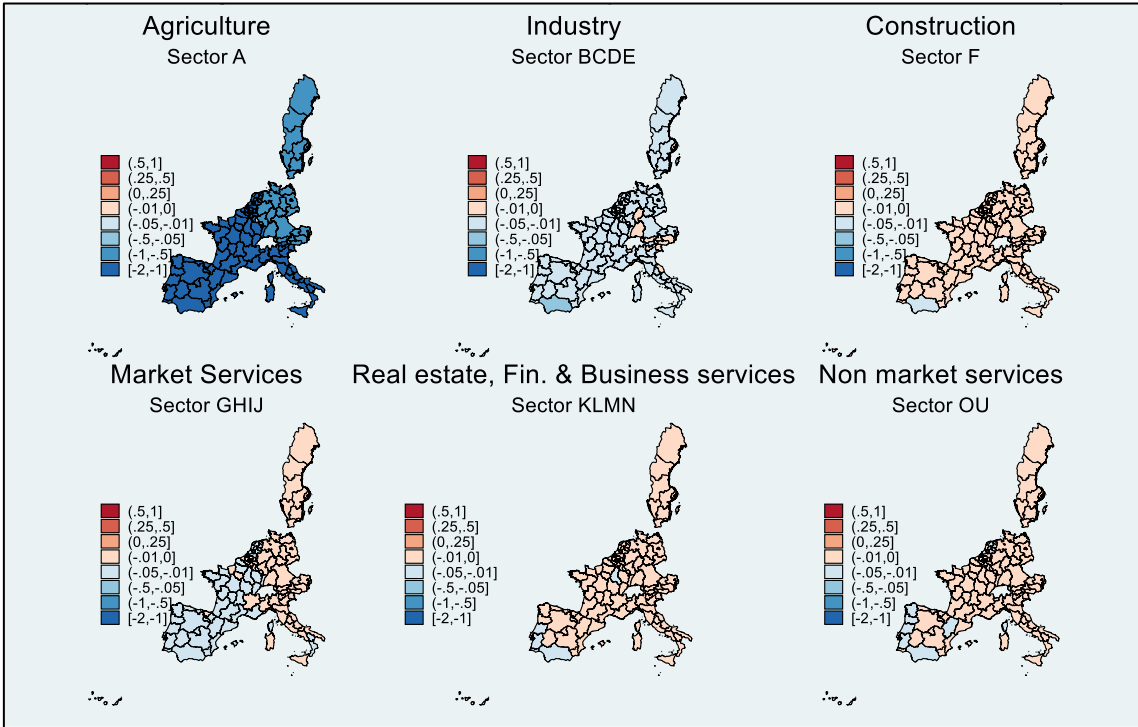
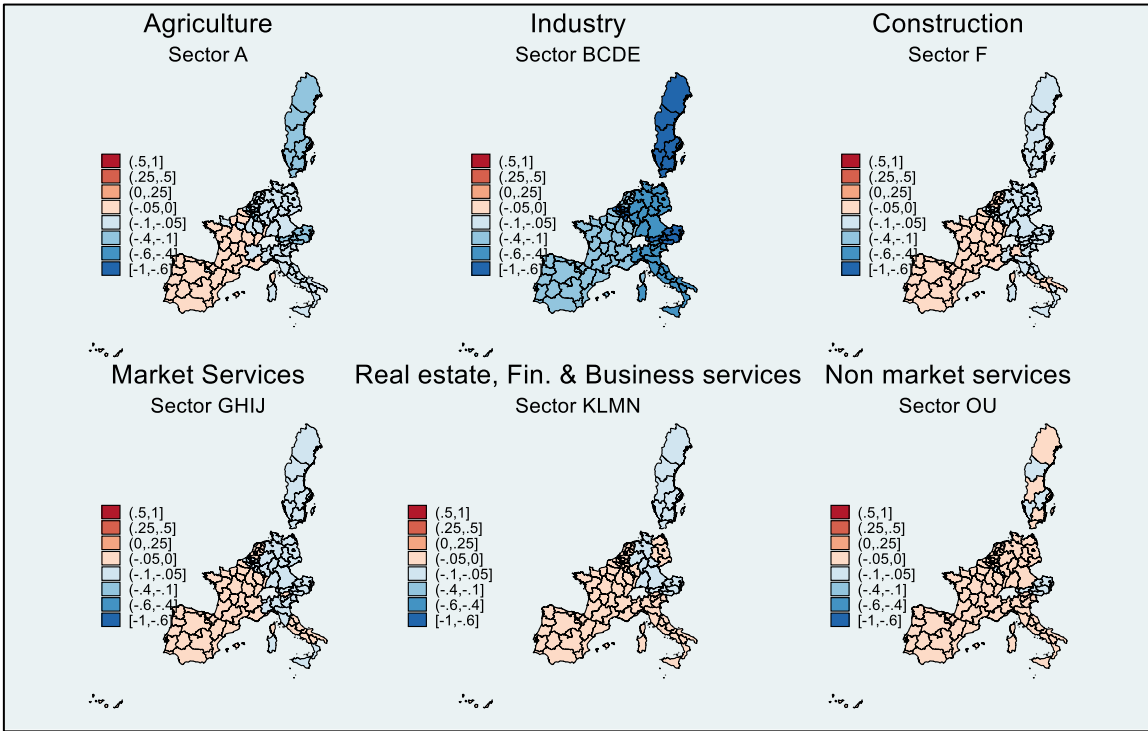


Figure 17. Output reductions due to a decrease in Industry caused by a reduction of imports of manufacturing products from Russia.



APPENDICES
to
Beyond Borders: How Spillovers and Commercial Networks
Shape European Productivity

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Appendix A. Elasticities of input factors and productivity change spillover.

The equivalent expressions of (12) and (13) when a Spatial Durbin production function with Hicks non-neutral technological progress is used respectively are:

$$E_{k-unneutral} = \Omega \begin{bmatrix} \alpha + \beta t & w_{12}\psi(t) & \dots & w_{1N}\psi(t) \\ w_{21}\psi(t) & \alpha + \beta t & \dots & w_{2N}\psi(t) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\psi(t) & w_{N2}\psi(t) & \dots & \alpha + \beta t \end{bmatrix}, \quad (\text{A.1})$$

where $\psi(t) = \phi - \rho\alpha + \varphi t - \beta\rho t$, and

$$g_{t-unneutral} = \Omega(TC_0 + TC_1 \ln k), \quad (\text{A.2})$$

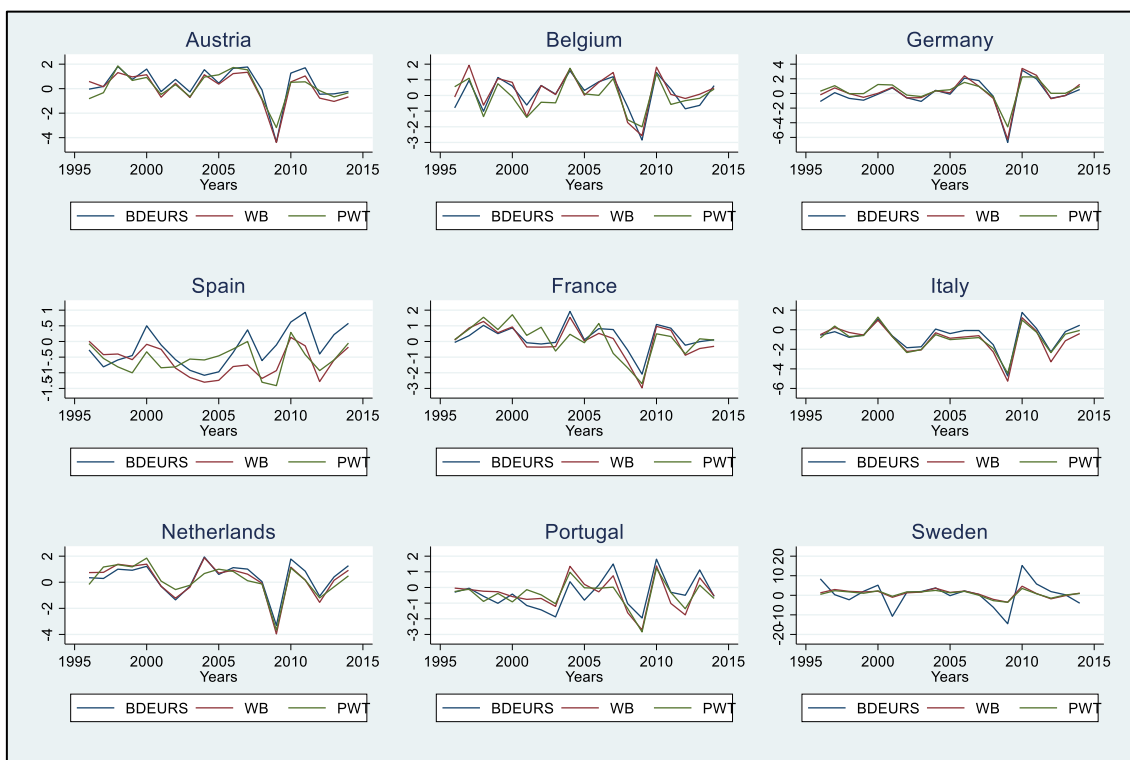
where Ω is the global multiplier, and

$$TC_0 = \begin{bmatrix} \frac{\partial R_t'}{\partial t} \delta_1 & 0 & \dots & 0 \\ 0 & \frac{\partial R_t'}{\partial t} \delta_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \frac{\partial R_t'}{\partial t} \delta_N \end{bmatrix}, \quad (\text{A.3})$$

and

$$TC_1 = \begin{bmatrix} \beta t & w_{12}(\varphi - \beta\rho) & \dots & w_{1N}(\varphi - \beta\rho) \\ w_{21}(\varphi - \beta\rho) & \beta t & \dots & w_{2N}(\varphi - \beta\rho) \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}(\varphi - \beta\rho) & w_{N2}(\varphi - \beta\rho) & \dots & \beta t \end{bmatrix}. \quad (\text{A.4})$$

Appendix B. Growth accounting TFP. Comparison with World Bank and PWT.



Note: Annual rate of growth in percentage.

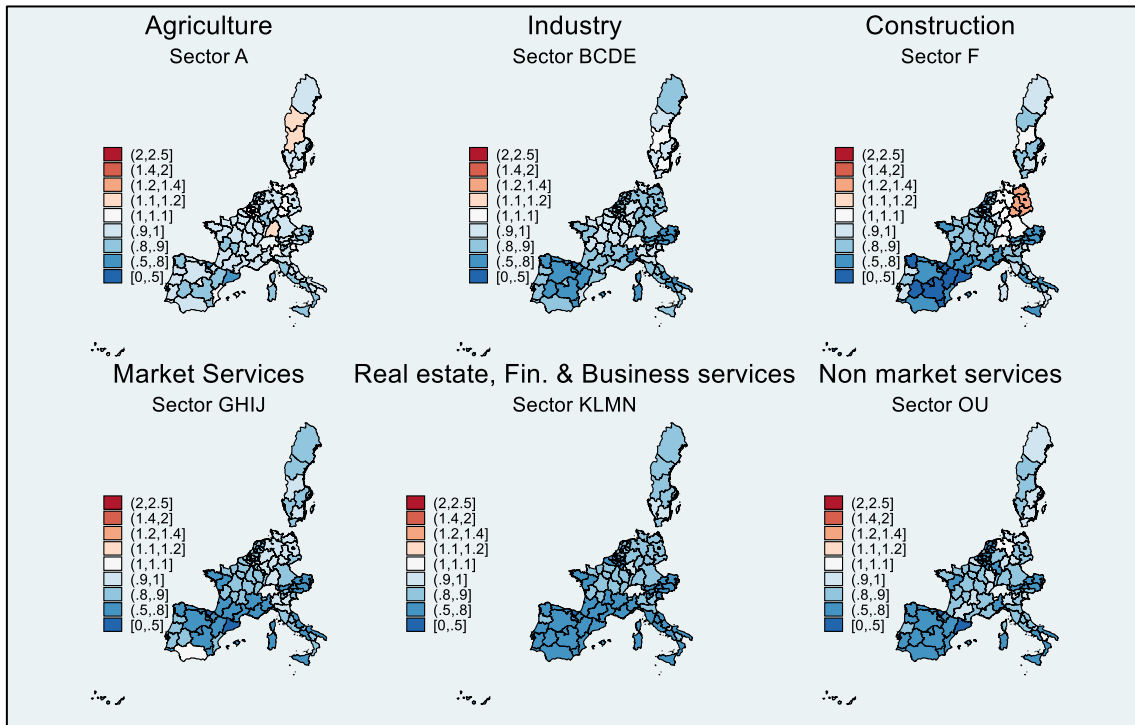
Appendix C. Sectoral disaggregation of the EUREGIO database.

The **EUREGIO** database provides interregional information on imports and exports for the following sectors:

EUREGIO		This paper	
SS1	Agriculture	Agriculture	Sector A
SS2	Mining, quarrying and energy supply	Industry	Sector BCDE
SS3	Food, beverages, and tobacco		
SS4	Textiles and Leather		
SS5	Coke, refined petroleum, nuclear, fuel and chemicals		
SS6 & SS7	Electrical, optical and transport equipment		
SS8	Other manufacturing		
SS9	Construction	Construction	Sector F
SS10	Distribution	Market services	Sector GHIJ
SS11	Hotels and restaurant		
SS12	Transport, storage, and communication		
SS13	Financial intermediation	Real estate, financial and business services	Sector KLMN
SS14	Real estate, renting, and business activities		
SS15	Non-Market Service	Non-Market Services	Sector OU

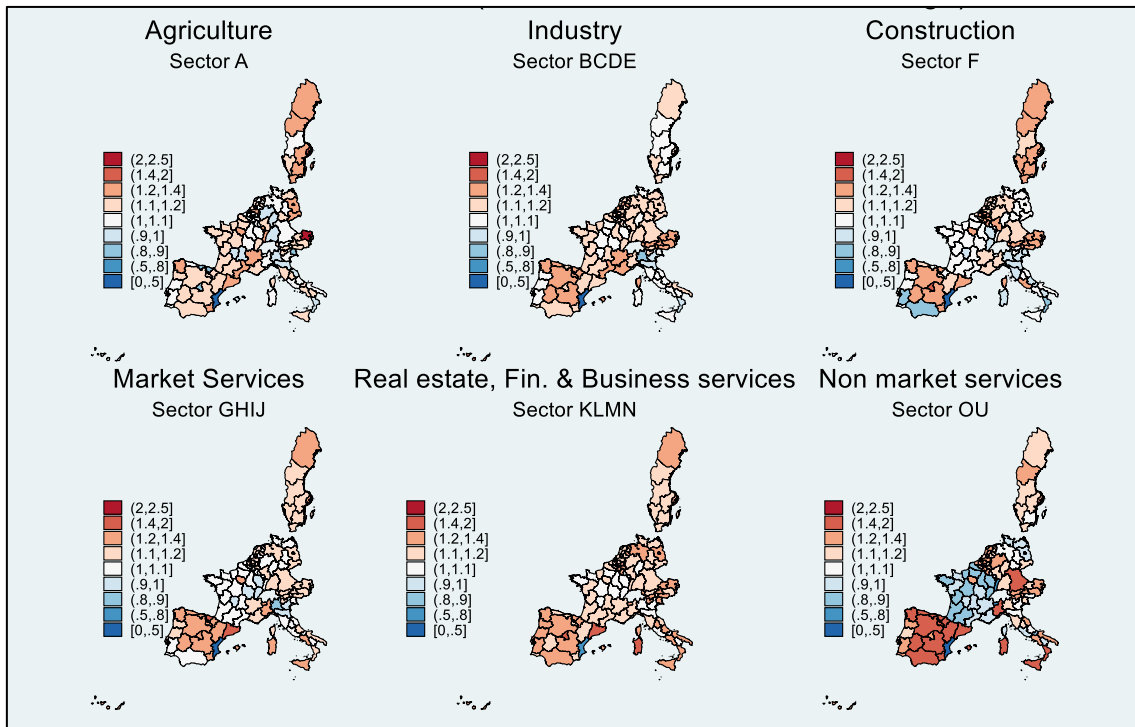
Appendix D. Trade size of each region-sector

a) Trade size in 2000.



Note: Trade size is measured as the row sum of the weight matrix of 2000. It is next expressed relative to the 2000-2010 average.

b) Trade size in 2010.



Note: Trade size is measured as the row sum of the weight matrix of 2010. It is next expressed relative to the 2000-2010 average.

Appendix E. Parameter estimates using a time-varying W matrix.

a) Hicks neutral specification

	SAR				SDM			
	2000		2010		2000		2010	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
lnk	0.422***	0.012	0.433***	0.012	0.426***	0.012	0.434***	0.012
W·lnk					0.001	0.001	0.000	0.000
t	-0.006***	0.001	-0.004***	0.001	-0.006***	0.001	-0.004***	0.001
W·lny	0.247***	0.001	0.212***	0.002	0.250***	0.001	0.211***	0.002
Agriculture	-0.516***	0.027	-0.539***	0.028	-0.524***	0.028	-0.540***	0.028
Industry	0.269***	0.027	0.253***	0.028	0.260***	0.028	0.252***	0.028
Construction	0.604***	0.029	0.611***	0.030	0.619***	0.030	0.612***	0.030
PM Services	0.223***	0.027	0.222***	0.028	0.223***	0.028	0.222***	0.028
RSFB Services	-0.013	0.035	-0.046	0.036	-0.016	0.037	-0.049	0.036
Austria	-0.263***	0.041	-0.264***	0.043	-0.275***	0.042	-0.265***	0.043
Belgium	-0.121***	0.039	-0.121***	0.041	-0.132***	0.040	-0.121***	0.041
Germany	-0.214***	0.037	-0.243***	0.038	-0.222***	0.038	-0.243***	0.038
Spain	-0.214***	0.036	-0.238***	0.038	-0.217***	0.038	-0.239***	0.038
France	-0.075**	0.035	-0.090**	0.036	-0.080**	0.036	-0.090**	0.036
Italy	-0.162***	0.035	-0.185***	0.036	-0.164***	0.036	-0.186***	0.037
Netherlands	-0.099**	0.039	-0.106***	0.040	-0.109***	0.040	-0.106***	0.040
Portugal	-0.344***	0.049	-0.413***	0.051	-0.340***	0.051	-0.413***	0.052
intercept	-0.023***	0.009	-0.014	0.009	-0.022**	0.009	-0.013	0.009
sigma	0.004		0.004		0.004		0.004	
R ²	0.796		0.786		0.794		0.785	
lnL	10873.3		10826.8		10961.7		10833.1	
Labor elasticity	0.578		0.567		0.574		0.566	

Notes: all models have been estimated using a RE estimator. The results for 2000 and 2010 indicate that the annual W matrices were normalized with the row-sum of the intermediate in 2000 and 2010, respectively. *(**)(***) stands for statistical significance at 10%(5%)(1%).

b) Hicks non-neutral specification

	SAR				SDM			
	2000		2010		2000		2010	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
lnk	0.405***	0.013	0.415***	0.014	0.407***	0.014	0.418***	0.014
W·lnk					0.004***	0.001	0.011***	0.001
lnk·t	0.003***	0.000	0.004***	0.000	0.004***	0.000	0.004***	0.000
W·lnk·t					-0.001***	0.000	-0.001***	0.000
t	-0.022***	0.004	-0.021***	0.004	-0.023***	0.004	-0.021***	0.005
W·lny	0.239***	0.001	0.211***	0.002	0.279***	0.002	0.249***	0.000
Agriculture	-0.519***	0.027	-0.543***	0.028	-0.518***	0.027	-0.538***	0.030
Industry	0.266***	0.027	0.249***	0.028	0.267***	0.028	0.258***	0.031
Construction	0.606***	0.029	0.615***	0.030	0.616***	0.030	0.607***	0.033
PM Services	0.222***	0.027	0.221***	0.028	0.224***	0.027	0.227***	0.030
RSFB Services	-0.011	0.037	-0.043	0.038	-0.011	0.038	-0.070*	0.040
Austria	-0.267***	0.041	-0.269***	0.042	-0.266***	0.042	-0.243***	0.046
Belgium	-0.124***	0.039	-0.126***	0.041	-0.126***	0.040	-0.105**	0.044
Germany	-0.218***	0.037	-0.247***	0.038	-0.211***	0.038	-0.224***	0.041
Spain	-0.218***	0.036	-0.240***	0.038	-0.204***	0.037	-0.223***	0.041
France	-0.078**	0.035	-0.092**	0.036	-0.073**	0.036	-0.079**	0.039
Italy	-0.165***	0.035	-0.185***	0.036	-0.155***	0.036	-0.175***	0.039
Netherlands	-0.104***	0.038	-0.111***	0.040	-0.101**	0.039	-0.083*	0.043
Portugal	-0.354***	0.049	-0.415***	0.051	-0.313***	0.051	-0.372***	0.055
intercept	0.075***	0.025	0.092***	0.026	0.073***	0.028	0.085***	0.031
sigma	0.004		0.004		0.004		0.004	
R ²	0.776		0.766		0.774		0.755	
lnL	11000.3		10977.1		11099.0		11167.2	
Labor elasticity	0.595		0.585		0.593		0.582	

Notes: all models have been estimated using a RE estimator. The results for 2000 and 2010 indicate that the annual W matrices were normalized with the row-sum of the intermediate in 2000 and 2010, respectively. *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix F. FE parameter estimates.

	FE-Hicks neutral				FE-Hicks non-neutral			
	SAR		SDM		SAR		SDM	
	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.	Coef.	s.e.
lnk	0.439***	0.010	0.431***	0.010	0.369***	0.011	0.312***	0.012
W·lnk			0.061**	0.024		0.000	0.139***	0.026
lnk·t					0.010***	0.001	0.017***	0.001
W·lnk·t						0.000	0.017***	0.001
W·lny	0.404***	0.014	0.389***	0.016	0.423***	0.014	0.402***	0.016
sigma	0.007		0.007		0.006		0.006	
R ²	0.244		0.349		0.2635		0.338	
lnL	16576.443		16580.133		16682.486		16756.679	

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix G. non-spatial parameter estimates.

	RE-Hicks neutral		RE-Hicks non-neutral	
	Coef.	s.e.	Coef.	s.e.
lnk	0.440***	0.009	0.418***	0.009
lnk·t			0.008***	0.000
t	-0.002***	0.001	-0.026***	0.003
Agriculture	-0.540***	0.055	-0.582***	0.057
Industry	0.248***	0.055	0.152**	0.057
Construction	0.544***	0.056	0.6670***	0.058
PM Services	0.226***	0.055	0.198***	0.057
RSFB Services	-0.108*	0.058	-0.079	0.060
Austria	-0.266***	0.085	-0.332***	0.088
Belgium	-0.107	0.081	-0.154*	0.084
Germany	-0.265***	0.076	-0.263***	0.078
Spain	-0.305***	0.075	-0.279***	0.078
France	-0.112	0.072	-0.127*	0.075
Italy	-0.258***	0.073	-0.215***	0.075
Netherlands	-0.112	0.080	-0.127	0.083
Portugal	-0.566***	0.100	-0.480***	0.104
intercept	0.166**	0.072	0.416***	0.078
R ²	0.772		0.768	

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix H. Computation of regional TFP change.

We show in this appendix that the estimated sectoral TFP growth rates should be weighted using value added shares if we aim to obtain a measure of regional TFP change. For notational ease, we first rewrite [Balk \(2016a, eq. 57\)](#) using a continuous-time framework. This author decomposes the change of aggregate valued-added TFP into four components that measure respectively the contribution of continuing production units to aggregate productivity change (*within* effect), the effect of changes in the relative size of each sector (*reallocation* effect), and the contribution of entering and exiting production units. With no entering and exiting sectors, and choosing zero arbitrary scalar (i.e. $a = 0$ in equation 57), we can express the change of region i 's TFP as follows:

$$dTFP_i = \sum_{j=1}^J \theta_i^j dTFP_i^j + \sum_{j=1}^J TFP_i^j d\theta_i^j, \quad (\text{H.1})$$

where

$$TFP_i^j = \frac{VA_i^j}{X_i^j}, \quad (\text{H.2})$$

$$TFP_i = \frac{VA_i}{X_i} = \frac{\sum_{j=1}^J VA_i^j}{\sum_{j=1}^J X_i^j}, \quad (\text{H.3})$$

and the TFP weights are given by [Balk \(2016a, eq 92\)](#). In this case, $\theta_i^j = X_i^j / X_i$.⁴⁷ If we next express (H.1) in terms of rates of growth, we get:

$$\frac{dTFP_i}{TFP_i} = \sum_{j=1}^J \frac{VA_i^j}{VA_i} \cdot \frac{dTFP_i^j}{TFP_i^j} + \sum_{j=1}^J \frac{VA_i^j}{VA_i} \cdot \frac{d\theta_i^j}{\theta_i^j} \quad (\text{H.4})$$

The first component at the right-hand side of the equality sign is the *within* effect and the second component is the *reallocation* effect. This equation indicates that weighting the individual TFP growth rates by the input shares X_i^j / X_i delivers aggregate TFP growth if, and only if, the relative size of each sector does not change over time.

⁴⁷ If the individual and aggregate value-added based price indices do not coincide, the appropriate weights are given by [Balk \(2016a, eq. 83\)](#). In this case, the input share θ_i^j should be adjusted by the ratio of these two value-added price indices. Our aggregate TFP growth rates are very similar regardless whether we use θ_i^j or its adjusted counterpart.

Appendix I. Direct, indirect, and total TFP growth rates. SAR model estimated using a RE estimator. Hicks neutral specification.

Agriculture						Agriculture					
Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered	Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.018 ***	0.003 ***	0.021 ***	0.002 ***	0.020 ***	FR41	0.008 ***	0.001 ***	0.009 ***	0.001 ***	0.009 ***
AT12	0.008 ***	0.002 ***	0.010 ***	0.002 ***	0.009 ***	FR42	-0.001 **	0.002 ***	0.000	0.000 **	-0.002 **
AT13	-0.033 ***	0.000	-0.033 ***	-0.001 ***	-0.034 ***	FR43	0.012 ***	0.000 ***	0.012 ***	0.001 ***	0.013 ***
AT21	0.008 ***	0.002 ***	0.011 ***	0.001 ***	0.009 ***	FR51	-0.012 ***	0.002 ***	-0.010 ***	-0.003 ***	-0.015 ***
AT22	0.021 ***	0.002 ***	0.023 ***	0.003 ***	0.024 ***	FR52	0.000	0.003 ***	0.003 ***	0.000	0.000
AT31	0.020 ***	0.002 ***	0.022 ***	0.003 ***	0.023 ***	FR53	0.005 ***	0.002 ***	0.007 ***	0.001 ***	0.006 ***
AT32	0.019 ***	0.002 ***	0.021 ***	0.001 ***	0.021 ***	FR61	-0.001 ***	0.002 ***	0.001 **	0.000 ***	-0.002 ***
AT33	0.007 ***	0.003 ***	0.010 ***	0.001 ***	0.007 ***	FR62	-0.009 ***	0.002 ***	-0.007 ***	-0.002 ***	-0.011 ***
AT34	0.027 ***	0.004 ***	0.031 ***	0.001 ***	0.029 ***	FR63	0.021 ***	0.001 ***	0.022 ***	0.002 ***	0.023 ***
BE10	0.004 ***	0.001 ***	0.004 ***	0.000 ***	0.004 ***	FR71	0.001 ***	0.002 ***	0.003 ***	0.000 ***	0.001 ***
BE21	0.008 ***	0.001 ***	0.010 ***	0.001 ***	0.009 ***	FR72	0.004 ***	0.001 ***	0.005 ***	0.000 ***	0.004 ***
BE22	0.013 ***	0.002 ***	0.015 ***	0.001 ***	0.014 ***	FR81	-0.001 ***	0.002 ***	0.001 **	0.000 ***	-0.002 ***
BE23	0.005 ***	0.002 ***	0.007 ***	0.001 ***	0.005 ***	FR82	-0.026 ***	0.002 ***	-0.024 ***	-0.006 ***	-0.032 ***
BE24	0.007 ***	0.002 ***	0.009 ***	0.000 ***	0.007 ***	FR83	-0.021 ***	0.004 ***	-0.017 ***	-0.002 ***	-0.022 ***
BE25	0.022 ***	0.002 ***	0.024 ***	0.003 ***	0.025 ***	ITC1	0.002 ***	-0.004 ***	-0.002 ***	0.000 ***	0.003 ***
BE31	0.013 ***	0.002 ***	0.015 ***	0.000 ***	0.013 ***	ITC2	0.013 ***	-0.003 ***	0.010 ***	0.000 ***	0.013 ***
BE32	0.003 ***	0.001 ***	0.004 ***	0.000 ***	0.003 ***	ITC3	-0.041 ***	-0.003 ***	-0.044 ***	-0.002 ***	-0.042 ***
BE33	-0.002 ***	0.002 ***	0.000 **	0.000 ***	-0.002 ***	ITC4	-0.006 ***	-0.004 ***	-0.009 ***	-0.002 ***	-0.008 ***
BE34	-0.007 ***	0.001 ***	-0.006 ***	0.000 ***	-0.007 ***	ITD1	0.017 ***	-0.003 ***	0.014 ***	0.000 ***	0.017 ***
BE35	-0.001 ***	0.001 ***	0.000	0.000 ***	-0.001 ***	ITD2	0.039 ***	-0.003 ***	0.036 ***	0.001 ***	0.040 ***
DE10	-0.022 ***	-0.001 ***	-0.023 ***	-0.005 ***	-0.027 ***	ITD3	0.001 ***	-0.002 ***	-0.001 ***	0.000 ***	0.002 ***
DE20	-0.006 ***	0.000	-0.005 ***	-0.002 ***	-0.007 ***	ITD4	-0.006 ***	-0.003 ***	-0.009 ***	0.000 ***	-0.007 ***
DE30	-0.116 ***	0.000	-0.116 ***	-0.002 ***	-0.119 ***	ITD5	0.016 ***	-0.003 ***	0.013 ***	0.004 ***	0.019 ***
DE40	-0.006 ***	0.003 ***	-0.003 ***	-0.001 ***	-0.007 ***	ITE1	0.008 ***	-0.003 ***	0.005 ***	0.001 ***	0.009 ***
DE50	-0.057 ***	-0.001 ***	-0.058 ***	-0.001 ***	-0.058 ***	ITE2	0.006 ***	-0.004 ***	0.002 ***	0.000 ***	0.006 ***
DE60	-0.030 ***	-0.002 ***	-0.031 ***	-0.001 ***	-0.030 ***	ITE3	-0.006 ***	-0.003 ***	-0.009 ***	0.000 ***	-0.006 ***
DE70	-0.016 ***	-0.001 ***	-0.017 ***	-0.002 ***	-0.017 ***	ITE4	0.007 ***	-0.003 ***	0.004 ***	0.001 ***	0.008 ***
DE80	-0.006 ***	0.001 ***	-0.004 ***	-0.001 ***	-0.006 ***	ITF1	-0.002 ***	-0.002 ***	-0.005 ***	0.000 ***	-0.003 ***
DE90	0.000	0.000 ***	0.000	0.000	0.000	ITF2	0.022 ***	-0.003 ***	0.018 ***	0.000 ***	0.022 ***
DEA0	-0.009 ***	0.000	-0.009 ***	-0.002 ***	-0.011 ***	ITF3	0.019 ***	-0.003 ***	0.016 ***	0.004 ***	0.023 ***
DEB0	-0.008 ***	0.000 ***	-0.008 ***	-0.001 ***	-0.009 ***	ITF4	-0.005 ***	-0.002 ***	-0.007 ***	-0.001 ***	-0.006 ***
DEC0	-0.026 ***	0.001 ***	-0.025 ***	0.000 ***	-0.026 ***	ITF5	0.010 ***	-0.003 ***	0.007 ***	0.000 ***	0.010 ***
DED0	-0.007 ***	0.003 ***	-0.004 ***	-0.001 ***	-0.008 ***	ITF6	-0.010 ***	-0.003 ***	-0.013 ***	-0.001 ***	-0.012 ***
DEE0	0.004 ***	0.004 ***	0.008 ***	0.000 ***	0.004 ***	ITG1	0.009 ***	-0.005 ***	0.004 ***	0.001 ***	0.010 ***
DEF0	-0.025 ***	-0.002 ***	-0.027 ***	-0.004 ***	-0.029 ***	ITG2	0.023 ***	-0.004 ***	0.019 ***	0.001 ***	0.024 ***
DEG0	-0.008 ***	0.003 ***	-0.005 ***	-0.001 ***	-0.008 ***	NL11	0.007 ***	0.008 ***	0.015 ***	0.001 ***	0.008 ***
ES11	0.015 ***	0.001 ***	0.016 ***	0.003 ***	0.019 ***	NL12	-0.018 ***	0.000 ***	-0.019 ***	-0.002 ***	-0.021 ***
ES12	0.003 ***	0.000 ***	0.003 ***	0.000 ***	0.003 ***	NL13	0.008 ***	-0.002 ***	0.006 ***	0.001 ***	0.008 ***
ES13	-0.026 ***	0.001 ***	-0.025 ***	-0.002 ***	-0.028 ***	NL21	-0.019 ***	0.000	-0.019 ***	-0.002 ***	-0.022 ***
ES21	-0.022 ***	0.005 ***	-0.018 ***	-0.002 ***	-0.024 ***	NL22	0.006 ***	0.000 ***	0.006 ***	0.001 ***	0.007 ***
ES22	0.015 ***	0.003 ***	0.018 ***	0.001 ***	0.016 ***	NL23	0.010 ***	0.000 ***	0.010 ***	0.001 ***	0.010 ***
ES23	-0.002 ***	0.003 ***	0.001 **	0.000 ***	-0.002 ***	NL31	-0.022 ***	0.000 ***	-0.022 ***	-0.002 ***	-0.023 ***
ES24	0.019 ***	0.001 ***	0.019 ***	0.002 ***	0.021 ***	NL32	-0.008 ***	0.000 ***	-0.008 ***	-0.001 ***	-0.009 ***
ES30	-0.036 ***	-0.001 ***	-0.037 ***	-0.001 ***	-0.038 ***	NL33	0.008 ***	0.000	0.008 ***	0.003 ***	0.011 ***
ES41	0.012 ***	0.001 ***	0.013 ***	0.003 ***	0.014 ***	NL34	0.027 ***	-0.002 ***	0.025 ***	0.002 ***	0.029 ***
ES42	0.003 ***	0.003 ***	0.005 ***	0.000 ***	0.003 ***	NL41	0.013 ***	0.001 ***	0.013 ***	0.003 ***	0.015 ***
ES43	0.017 ***	0.004 ***	0.021 ***	0.002 ***	0.019 ***	NL42	0.005 ***	0.000 ***	0.004 ***	0.001 ***	0.006 ***
ES51	0.009 ***	0.001 ***	0.010 ***	0.001 ***	0.009 ***	PT11	-0.009 ***	-0.003 ***	-0.012 ***	-0.002 ***	-0.011 ***
ES52	0.009 ***	0.000 ***	0.009 ***	0.002 ***	0.012 ***	PT15	-0.034 ***	-0.003 ***	-0.036 ***	-0.004 ***	-0.038 ***
ES53	-0.045 ***	-0.003 ***	-0.048 ***	-0.003 ***	-0.048 ***	PT16	-0.009 ***	-0.002 ***	-0.011 ***	-0.002 ***	-0.011 ***
ES61	0.016 ***	0.000 ***	0.016 ***	0.010 ***	0.026 ***	PT17	-0.039 ***	-0.001 ***	-0.040 ***	-0.003 ***	-0.041 ***
ES62	-0.029 ***	-0.001 ***	-0.030 ***	-0.004 ***	-0.033 ***	PT18	-0.037 ***	-0.001 ***	-0.038 ***	-0.007 ***	-0.045 ***
ES70	-0.005 ***	0.000 ***	-0.006 ***	0.000 ***	-0.006 ***	SE11	0.018 ***	0.005 ***	0.023 ***	0.000 ***	0.018 ***
FR10	-0.003 ***	0.001 ***	-0.003 ***	-0.001 ***	-0.004 ***	SE12	0.006 ***	0.004 ***	0.010 ***	0.000 ***	0.006 ***
FR21	-0.010 ***	0.002 ***	-0.009 ***	-0.002 ***	-0.012 ***	SE21	-0.002 ***	0.003 ***	0.001 ***	0.000 ***	-0.002 ***
FR22	-0.003 ***	0.001 ***	-0.002 ***	-0.001 ***	-0.004 ***	SE22	-0.016 ***	0.002 ***	-0.015 ***	-0.002 ***	-0.018 ***
FR23	0.001 **	0.003 ***	0.003 ***	0.000 **	0.001 **	SE23	-0.004 ***	0.001 ***	-0.002 ***	-0.001 ***	-0.005 ***
FR24	-0.006 ***	0.001 ***	-0.004 ***	-0.001 ***	-0.007 ***	SE31	0.004 ***	0.002 ***	0.006 ***	0.000 ***	0.004 ***
FR25	-0.001 ***	0.002 ***	0.001 ***	0.000 ***	-0.001 ***	SE32	0.018 ***	0.002 ***	0.019 ***	0.001 ***	0.018 ***
FR26	-0.007 ***	0.002 ***	-0.005 ***	-0.001 ***	-0.008 ***	SE33	-0.025 ***	0.006 ***	-0.019 ***	-0.002 ***	-0.027 ***
FR30	-0.014 ***	0.001 ***	-0.013 ***	-0.003 ***	-0.016 ***						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Country-Region	Construction					Country-Region	Construction				
	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered		Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.013 ***	0.000 ***	0.013 ***	0.008 ***	0.021 ***	FR41	0.008 ***	-0.001 ***	0.007 ***	0.013 ***	0.021 ***
AT12	0.009 ***	0.000 ***	0.009 ***	0.014 ***	0.023 ***	FR42	0.012 ***	-0.001 ***	0.011 ***	0.017 ***	0.029 ***
AT13	0.007 ***	-0.002 ***	0.005 ***	0.011 ***	0.017 ***	FR43	0.003 ***	-0.001 ***	0.003 ***	0.003 ***	0.006 ***
AT21	0.011 ***	-0.001 ***	0.010 ***	0.009 ***	0.020 ***	FR51	0.009 ***	-0.001 ***	0.008 ***	0.017 ***	0.026 ***
AT22	0.011 ***	-0.001 ***	0.011 ***	0.014 ***	0.025 ***	FR52	0.013 ***	0.000 ***	0.012 ***	0.018 ***	0.031 ***
AT31	0.010 ***	0.000 ***	0.010 ***	0.016 ***	0.026 ***	FR53	0.015 ***	-0.001 ***	0.014 ***	0.016 ***	0.031 ***
AT32	0.005 ***	0.000 ***	0.005 ***	0.005 ***	0.010 ***	FR61	0.013 ***	-0.001 ***	0.012 ***	0.017 ***	0.030 ***
AT33	0.015 ***	-0.001 ***	0.014 ***	0.015 ***	0.030 ***	FR62	0.015 ***	-0.001 ***	0.014 ***	0.019 ***	0.033 ***
AT34	0.018 ***	-0.001 ***	0.017 ***	0.017 ***	0.035 ***	FR63	0.009 ***	-0.001 ***	0.008 ***	0.007 ***	0.016 ***
BE10	0.008 ***	-0.001 ***	0.007 ***	0.014 ***	0.021 ***	FR71	0.012 ***	-0.001 ***	0.011 ***	0.039 ***	0.051 ***
BE21	0.010 ***	-0.001 ***	0.009 ***	0.027 ***	0.037 ***	FR72	0.008 ***	0.000 ***	0.007 ***	0.011 ***	0.019 ***
BE22	0.008 ***	0.000 ***	0.008 ***	0.008 ***	0.016 ***	FR81	0.010 ***	0.000 ***	0.010 ***	0.014 ***	0.024 ***
BE23	0.012 ***	0.000 ***	0.012 ***	0.018 ***	0.030 ***	FR82	0.013 ***	-0.001 ***	0.013 ***	0.041 ***	0.054 ***
BE24	0.008 ***	0.000 ***	0.008 ***	0.011 ***	0.019 ***	FR83	0.016 ***	0.001 ***	0.017 ***	0.006 ***	0.022 ***
BE25	0.009 ***	0.000 ***	0.009 ***	0.014 ***	0.023 ***	ITC1	-0.010 ***	-0.002 ***	-0.013 ***	-0.048 ***	-0.059 ***
BE31	0.029 ***	-0.001 ***	0.028 ***	0.014 ***	0.043 ***	ITC2	0.015 ***	-0.004 ***	0.012 ***	0.002 ***	0.017 ***
BE32	0.005 ***	-0.001 ***	0.004 ***	0.004 ***	0.009 ***	ITC3	-0.004 ***	-0.003 ***	-0.007 ***	-0.003 ***	-0.007 ***
BE33	0.010 ***	-0.001 ***	0.010 ***	0.013 ***	0.024 ***	ITC4	-0.005 ***	-0.004 ***	-0.009 ***	-0.031 ***	-0.035 ***
BE34	-0.002 ***	-0.001 ***	-0.003 ***	-0.001 ***	-0.003 ***	ITD1	0.013 ***	-0.003 ***	0.010 ***	0.005 ***	0.018 ***
BE35	0.001 ***	0.000 ***	0.001 ***	0.001 ***	0.002 ***	ITD2	-0.003 ***	-0.003 ***	-0.006 ***	-0.001 ***	-0.003 ***
DE10	0.000	-0.001 ***	-0.001 ***	-0.003	-0.003	ITD3	-0.002 ***	-0.003 ***	-0.006 ***	-0.009 ***	-0.012 ***
DE20	0.005 ***	0.000 ***	0.004 ***	0.029 ***	0.033 ***	ITD4	-0.002 ***	-0.003 ***	-0.005 ***	-0.002 ***	-0.005 ***
DE30	0.003 ***	-0.001 ***	0.002 ***	0.005 ***	0.008 ***	ITD5	-0.005 ***	-0.003 ***	-0.008 ***	-0.017 ***	-0.022 ***
DE40	0.021 ***	0.000 ***	0.021 ***	0.025 ***	0.046 ***	ITE1	-0.007 ***	-0.003 ***	-0.011 ***	-0.020 ***	-0.028 ***
DE50	-0.004 ***	0.000	-0.004 ***	-0.005 ***	-0.009 ***	ITE2	-0.010 ***	-0.004 ***	-0.013 ***	-0.006 ***	-0.015 ***
DE60	-0.003 ***	-0.001 ***	-0.004 ***	-0.007 ***	-0.010 ***	ITE3	-0.003 ***	-0.004 ***	-0.006 ***	-0.006 ***	-0.006 ***
DE70	-0.002 ***	-0.001 ***	-0.003 ***	-0.009 ***	-0.012 ***	ITE4	-0.006 ***	-0.003 ***	-0.010 ***	-0.020 ***	-0.027 ***
DE80	0.019 ***	-0.001 ***	0.018 ***	0.016 ***	0.035 ***	ITF1	0.002 ***	-0.003 ***	-0.001 ***	0.002 ***	0.004 ***
DE90	0.002 ***	0.000 ***	0.002 ***	0.008 ***	0.010 ***	ITF2	-0.006 ***	-0.004 ***	-0.009 ***	-0.001 ***	-0.007 ***
DEA0	0.002 ***	-0.001 ***	0.002 ***	0.016 ***	0.018 ***	ITF3	-0.008 ***	-0.002 ***	-0.011 ***	-0.022 ***	-0.031 ***
DEB0	0.002 ***	-0.001 ***	0.001 ***	0.003 ***	0.005 ***	ITF4	-0.003 ***	-0.003 ***	-0.006 ***	-0.006 ***	-0.009 ***
DEC0	0.011 ***	0.000 ***	0.011 ***	0.014 ***	0.025 ***	ITF5	0.020 ***	-0.004 ***	0.017 ***	0.007 ***	0.027 ***
DED0	0.019 ***	0.000 ***	0.019 ***	0.033 ***	0.052 ***	ITF6	-0.009 ***	-0.003 ***	-0.012 ***	-0.008 ***	-0.017 ***
DEE0	0.028 ***	0.000	0.028 ***	0.035 ***	0.063 ***	ITG1	-0.021 ***	-0.002 ***	-0.023 ***	-0.044 ***	-0.065 ***
DEF0	-0.004 ***	-0.001 ***	-0.005 ***	-0.006 ***	-0.010 ***	ITG2	-0.005 ***	-0.003 ***	-0.008 ***	-0.005 ***	-0.010 ***
DEG0	0.017 ***	0.000 ***	0.017 ***	0.022 ***	0.039 ***	NL11	0.054 ***	-0.001 ***	0.053 ***	0.057 ***	0.111 ***
ES11	0.012 ***	-0.003 ***	0.009 ***	0.023 ***	0.035 ***	NL12	0.001 ***	-0.001 ***	0.000	0.001 ***	0.002 ***
ES12	0.004 ***	-0.002 ***	0.001 ***	0.004 ***	0.008 ***	NL13	-0.020 ***	0.000 ***	-0.020 ***	-0.012 ***	-0.032 ***
ES13	0.007 ***	-0.003 ***	0.004 ***	0.006 ***	0.013 ***	NL21	0.000	0.000 ***	0.000 ***	0.000	0.000
ES21	0.020 ***	-0.002 ***	0.018 ***	0.031 ***	0.052 ***	NL22	0.002 ***	0.000 ***	0.001 ***	0.002 ***	0.004 ***
ES22	0.017 ***	-0.002 ***	0.014 ***	0.022 ***	0.039 ***	NL23	-0.008 ***	0.001 ***	-0.008 ***	-0.003 ***	-0.011 ***
ES23	0.019 ***	-0.003 ***	0.016 ***	0.014 ***	0.033 ***	NL31	-0.005 ***	0.000 ***	-0.005 ***	-0.005 ***	-0.011 ***
ES24	0.013 ***	-0.002 ***	0.010 ***	0.019 ***	0.031 ***	NL32	-0.009 ***	0.001 ***	-0.007 ***	-0.022 ***	-0.031 ***
ES30	-0.004 ***	-0.002 ***	-0.006 ***	-0.020 ***	-0.024 ***	NL33	-0.005 ***	0.001 ***	-0.004 ***	-0.014 ***	-0.018 ***
ES41	0.013 ***	-0.003 ***	0.010 ***	0.028 ***	0.041 ***	NL34	-0.014 ***	0.000 ***	-0.014 ***	-0.009 ***	-0.023 ***
ES42	0.021 ***	-0.003 ***	0.018 ***	0.033 ***	0.054 ***	NL41	0.003 ***	0.000 ***	0.003 ***	0.008 ***	0.010 ***
ES43	0.030 ***	-0.001 ***	0.029 ***	0.017 ***	0.047 ***	NL42	-0.002 ***	0.000 ***	-0.003 ***	-0.002 ***	-0.005 ***
ESS1	0.009 ***	-0.002 ***	0.007 ***	0.018 ***	0.027 ***	PT11	0.003 ***	-0.005 ***	-0.002 ***	0.005 ***	0.009 ***
ESS2	0.010 ***	-0.003 ***	0.007 ***	0.034 ***	0.044 ***	PT15	-0.002 ***	-0.006 ***	-0.008 ***	-0.001 ***	-0.003 ***
ESS3	0.010 ***	-0.006 ***	0.005 ***	0.007 ***	0.017 ***	PT16	0.003 ***	-0.004 ***	-0.002 ***	0.004 ***	0.007 ***
ES61	0.003 ***	-0.001 ***	0.003 ***	0.009 ***	0.012 ***	PT17	0.006 ***	-0.004 ***	0.002 ***	0.014 ***	0.019 ***
ES62	-0.002 ***	-0.004 ***	-0.005 ***	-0.002 ***	-0.003 ***	PT18	0.002 ***	-0.005 ***	-0.003 ***	0.002 ***	0.004 ***
ES70	0.017 ***	-0.004 ***	0.013 ***	0.014 ***	0.031 ***	SE11	0.028 ***	-0.001 ***	0.027 ***	0.060 ***	0.088 ***
FR10	0.005 ***	0.000 ***	0.006 ***	0.032 ***	0.038 ***	SE12	0.016 ***	-0.002 ***	0.014 ***	0.027 ***	0.043 ***
FR21	0.010 ***	-0.001 ***	0.009 ***	0.014 ***	0.024 ***	SE21	0.006 ***	-0.002 ***	0.004 ***	0.006 ***	0.012 ***
FR22	0.006 ***	-0.001 ***	0.005 ***	0.008 ***	0.014 ***	SE22	0.006 ***	-0.002 ***	0.004 ***	0.008 ***	0.014 ***
FR23	0.015 ***	-0.001 ***	0.015 ***	0.025 ***	0.041 ***	SE23	0.013 ***	-0.002 ***	0.011 ***	0.021 ***	0.034 ***
FR24	0.010 ***	-0.001 ***	0.009 ***	0.014 ***	0.024 ***	SE31	0.003 ***	-0.002 ***	0.001 ***	0.003 ***	0.006 ***
FR25	0.012 ***	-0.001 ***	0.012 ***	0.016 ***	0.028 ***	SE32	0.005 ***	-0.001 ***	0.004 ***	0.005 ***	0.010 ***
FR26	0.006 ***	0.000 ***	0.006 ***	0.007 ***	0.013 ***	SE33	0.025 ***	-0.004 ***	0.021 ***	0.022 ***	0.047 ***
FR30	0.005 ***	-0.001 ***	0.004 ***	0.009 ***	0.014 ***						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Industry						Industry					
Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered	Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.000	0.002 ***	0.002 ***	0.000	0.000	FR41	-0.020 ***	-0.001 ***	-0.021 ***	-0.004 ***	-0.024 ***
AT12	-0.005 ***	0.001 ***	-0.004 ***	-0.002 ***	-0.007 ***	FR42	-0.016 ***	0.000 ***	-0.017 ***	-0.003 ***	-0.020 ***
AT13	-0.007 ***	-0.001 ***	-0.008 ***	-0.003 ***	-0.010 ***	FR43	-0.023 ***	-0.001 ***	-0.024 ***	-0.003 ***	-0.026 ***
AT21	-0.007 ***	0.000	-0.007 ***	-0.001 ***	-0.009 ***	FR51	-0.018 ***	0.000 ***	-0.018 ***	-0.004 ***	-0.022 ***
AT22	-0.004 ***	0.001 ***	-0.003 ***	-0.001 ***	-0.005 ***	FR52	-0.023 ***	0.001 ***	-0.022 ***	-0.004 ***	-0.027 ***
AT31	-0.007 ***	0.001 ***	-0.005 ***	-0.002 ***	-0.009 ***	FR53	-0.021 ***	0.001 ***	-0.020 ***	-0.003 ***	-0.024 ***
AT32	-0.008 ***	0.000 ***	-0.007 ***	-0.002 ***	-0.009 ***	FR61	-0.019 ***	0.001 ***	-0.018 ***	-0.004 ***	-0.023 ***
AT33	-0.011 ***	0.001 ***	-0.010 ***	-0.003 ***	-0.013 ***	FR62	-0.020 ***	0.001 ***	-0.019 ***	-0.004 ***	-0.024 ***
AT34	-0.010 ***	0.002 ***	-0.009 ***	-0.002 ***	-0.012 ***	FR63	-0.026 ***	-0.001 ***	-0.026 ***	-0.003 ***	-0.029 ***
BE10	-0.007 ***	-0.001 ***	-0.008 ***	-0.002 ***	-0.009 ***	FR71	-0.018 ***	0.001 ***	-0.017 ***	-0.005 ***	-0.023 ***
BE21	0.002 ***	-0.001 ***	0.001 ***	0.001 ***	0.004 ***	FR72	-0.021 ***	0.000 ***	-0.020 ***	-0.002 ***	-0.023 ***
BE22	0.002 ***	-0.001 ***	0.001 ***	0.000 ***	0.002 ***	FR81	-0.018 ***	0.001 ***	-0.017 ***	-0.003 ***	-0.021 ***
BE23	0.002 ***	-0.001 ***	0.002 ***	0.001 ***	0.003 ***	FR82	-0.016 ***	0.000 ***	-0.015 ***	-0.004 ***	-0.019 ***
BE24	-0.004 ***	-0.001 ***	-0.005 ***	-0.001 ***	-0.005 ***	FR83	-0.006 ***	0.001 ***	-0.005 ***	-0.001 ***	-0.007 ***
BE25	0.003 ***	0.000 ***	0.002 ***	0.001 ***	0.003 ***	ITC1	-0.011 ***	-0.004 ***	-0.015 ***	-0.004 ***	-0.014 ***
BE31	-0.003 ***	-0.001 ***	-0.004 ***	0.000 ***	-0.004 ***	ITC2	-0.031 ***	-0.004 ***	-0.035 ***	-0.001 ***	-0.032 ***
BE32	-0.003 ***	-0.001 ***	-0.005 ***	-0.001 ***	-0.004 ***	ITC3	0.007 ***	-0.005 ***	0.002 ***	0.001 ***	0.008 ***
BE33	0.005 ***	-0.001 ***	0.004 ***	0.002 ***	0.007 ***	ITC4	-0.019 ***	-0.004 ***	-0.024 ***	-0.017 ***	-0.036 ***
BE34	0.004 ***	-0.002 ***	0.002 ***	0.000 ***	0.004 ***	ITD1	-0.006 ***	-0.004 ***	-0.010 ***	0.000 ***	-0.006 ***
BE35	0.003 ***	-0.002 ***	0.001 ***	0.000 ***	0.004 ***	ITD2	-0.022 ***	-0.004 ***	-0.026 ***	-0.001 ***	-0.023 ***
DE10	-0.004 ***	-0.003 ***	-0.006 ***	-0.002 ***	-0.005 ***	ITD3	-0.020 ***	-0.004 ***	-0.024 ***	-0.009 ***	-0.030 ***
DE20	-0.002 ***	-0.001 ***	-0.003 ***	-0.001 ***	-0.003 ***	ITD4	-0.021 ***	-0.004 ***	-0.025 ***	-0.002 ***	-0.023 ***
DE30	-0.009 ***	-0.001 ***	-0.010 ***	-0.002 ***	-0.010 ***	ITD5	-0.004 ***	-0.005 ***	-0.008 ***	-0.002 ***	-0.005 ***
DE40	-0.017 ***	0.002 ***	-0.016 ***	-0.005 ***	-0.023 ***	ITE1	-0.021 ***	-0.005 ***	-0.026 ***	-0.007 ***	-0.028 ***
DE50	0.010 ***	-0.003 ***	0.007 ***	0.001 ***	0.012 ***	ITE2	-0.019 ***	-0.004 ***	-0.024 ***	-0.001 ***	-0.020 ***
DE60	-0.006 ***	-0.003 ***	-0.006 ***	-0.001 ***	-0.004 ***	ITE3	-0.016 ***	-0.005 ***	-0.020 ***	-0.002 ***	-0.017 ***
DE70	-0.010 ***	-0.003 ***	-0.013 ***	-0.004 ***	-0.014 ***	ITE4	-0.027 ***	-0.005 ***	-0.031 ***	-0.014 ***	-0.041 ***
DE80	-0.011 ***	0.001 ***	-0.010 ***	-0.002 ***	-0.013 ***	ITF1	-0.037 ***	-0.004 ***	-0.041 ***	-0.004 ***	-0.041 ***
DE90	-0.005 ***	-0.002 ***	-0.007 ***	-0.002 ***	-0.007 ***	ITF2	-0.018 ***	-0.004 ***	-0.022 ***	0.000 ***	-0.018 ***
DEA0	-0.006 ***	-0.002 ***	-0.008 ***	-0.005 ***	-0.011 ***	ITF3	-0.011 ***	-0.004 ***	-0.016 ***	-0.004 ***	-0.017 ***
DEB0	-0.007 ***	-0.002 ***	-0.008 ***	-0.002 ***	-0.008 ***	ITF4	-0.028 ***	-0.004 ***	-0.032 ***	-0.010 ***	-0.038 ***
DEC0	-0.007 ***	-0.001 ***	-0.008 ***	-0.001 ***	-0.008 ***	ITF5	-0.033 ***	-0.004 ***	-0.037 ***	-0.002 ***	-0.035 ***
DED0	-0.012 ***	0.001 ***	-0.011 ***	-0.004 ***	-0.016 ***	ITF6	-0.035 ***	-0.004 ***	-0.038 ***	-0.006 ***	-0.040 ***
DEE0	-0.012 ***	0.002 ***	-0.010 ***	-0.003 ***	-0.011 ***	ITG1	-0.021 ***	-0.004 ***	-0.025 ***	-0.005 ***	-0.026 ***
DEF0	0.001 ***	-0.004 ***	-0.002 ***	0.000 ***	0.002 ***	ITG2	-0.018 ***	-0.005 ***	-0.023 ***	-0.003 ***	-0.021 ***
DEG0	-0.013 ***	0.001 ***	-0.012 ***	-0.003 ***	-0.016 ***	NL11	-0.020 ***	-0.001 ***	-0.020 ***	-0.005 ***	-0.024 ***
ES11	-0.034 ***	0.000 ***	-0.034 ***	-0.008 ***	-0.042 ***	NL12	-0.022 ***	-0.003 ***	-0.025 ***	-0.005 ***	-0.027 ***
ES12	-0.047 ***	0.000 ***	-0.048 ***	-0.010 ***	-0.058 ***	NL13	-0.021 ***	-0.004 ***	-0.025 ***	-0.004 ***	-0.025 ***
ES13	-0.035 ***	-0.001 ***	-0.036 ***	-0.005 ***	-0.040 ***	NL21	-0.013 ***	-0.003 ***	-0.015 ***	-0.004 ***	-0.017 ***
ES21	-0.028 ***	0.004 ***	-0.023 ***	-0.001 ***	-0.029 ***	NL22	-0.014 ***	-0.002 ***	-0.016 ***	-0.006 ***	-0.020 ***
ES22	-0.032 ***	0.002 ***	-0.031 ***	-0.006 ***	-0.038 ***	NL23	-0.022 ***	-0.001 ***	-0.023 ***	-0.002 ***	-0.024 ***
ES23	-0.047 ***	0.001 ***	-0.046 ***	-0.005 ***	-0.052 ***	NL31	-0.012 ***	-0.002 ***	-0.014 ***	-0.004 ***	-0.016 ***
ES24	-0.036 ***	0.001 ***	-0.035 ***	-0.010 ***	-0.046 ***	NL32	-0.023 ***	0.000 ***	-0.023 ***	-0.011 ***	-0.034 ***
ES30	-0.059 ***	0.000 ***	-0.060 ***	-0.036 ***	-0.095 ***	NL33	-0.021 ***	-0.001 ***	-0.022 ***	-0.012 ***	-0.033 ***
ES41	-0.039 ***	0.001 ***	-0.039 ***	-0.018 ***	-0.057 ***	NL34	-0.015 ***	-0.003 ***	-0.018 ***	-0.002 ***	-0.017 ***
ES42	-0.041 ***	0.002 ***	-0.040 ***	-0.010 ***	-0.052 ***	NL41	-0.019 ***	-0.001 ***	-0.020 ***	-0.010 ***	-0.029 ***
ES43	-0.034 ***	0.001 ***	-0.033 ***	-0.004 ***	-0.038 ***	NL42	-0.018 ***	-0.002 ***	-0.020 ***	-0.004 ***	-0.022 ***
ES51	-0.053 ***	0.000 ***	-0.053 ***	-0.001 ***	-0.054 ***	PT11	-0.024 ***	-0.004 ***	-0.028 ***	-0.010 ***	-0.034 ***
ES52	-0.028 ***	-0.001 ***	-0.029 ***	-0.025 ***	-0.053 ***	PT15	-0.054 ***	-0.005 ***	-0.060 ***	-0.009 ***	-0.063 ***
ES53	-0.046 ***	-0.001 ***	-0.048 ***	-0.014 ***	-0.060 ***	PT16	-0.029 ***	-0.004 ***	-0.033 ***	-0.010 ***	-0.039 ***
ES61	-0.042 ***	0.000 ***	-0.042 ***	-0.001 ***	-0.043 ***	PT17	-0.040 ***	-0.002 ***	-0.042 ***	-0.016 ***	-0.056 ***
ES62	-0.040 ***	-0.002 ***	-0.042 ***	-0.007 ***	-0.048 ***	PT18	-0.056 ***	-0.004 ***	-0.061 ***	-0.011 ***	-0.067 ***
ES70	-0.046 ***	0.000 ***	-0.046 ***	-0.018 ***	-0.064 ***	SE11	-0.030 ***	0.002 ***	-0.028 ***	-0.008 ***	-0.037 ***
FR10	-0.014 ***	0.001 ***	-0.013 ***	-0.011 ***	-0.025 ***	SE12	-0.038 ***	0.000 ***	-0.038 ***	-0.008 ***	-0.046 ***
FR21	-0.021 ***	-0.001 ***	-0.022 ***	-0.003 ***	-0.024 ***	SE21	-0.029 ***	-0.003 ***	-0.032 ***	-0.007 ***	-0.036 ***
FR22	-0.021 ***	-0.001 ***	-0.022 ***	-0.003 ***	-0.024 ***	SE22	-0.026 ***	-0.002 ***	-0.028 ***	-0.006 ***	-0.032 ***
FR23	-0.020 ***	0.001 ***	-0.019 ***	-0.003 ***	-0.023 ***	SE23	-0.033 ***	-0.001 ***	-0.034 ***	-0.015 ***	-0.048 ***
FR24	-0.020 ***	0.000 ***	-0.021 ***	-0.004 ***	-0.024 ***	SE31	-0.042 ***	-0.002 ***	-0.044 ***	-0.006 ***	-0.048 ***
FR25	-0.021 ***	0.001 ***	-0.021 ***	-0.003 ***	-0.024 ***	SE32	-0.042 ***	0.000 ***	-0.041 ***	-0.003 ***	-0.045 ***
FR26	-0.021 ***	0.000 ***	-0.021 ***	-0.003 ***	-0.024 ***	SE33	-0.041 ***	0.000 ***	-0.041 ***	-0.007 ***	-0.047 ***
FR30	-0.013 ***	0.000 ***	-0.013 ***	-0.003 ***	-0.016 ***						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

PM Services						PM Services					
Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered	Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.004 ***	0.002 ***	0.006 ***	0.001 ***	0.005 ***	FR41	-0.001 ***	-0.001 ***	-0.002 ***	-0.001 ***	-0.002 ***
AT12	-0.002 ***	0.002 ***	0.000 **	-0.002 ***	-0.004 ***	FR42	0.000 ***	0.000 ***	-0.001 ***	0.000 ***	-0.001 ***
AT13	-0.007 ***	0.000 ***	-0.006 ***	-0.007 ***	-0.014 ***	FR43	-0.006 ***	-0.001 ***	-0.006 ***	-0.003 ***	-0.008 ***
AT21	-0.003 ***	0.001 ***	-0.002 ***	-0.001 ***	-0.004 ***	FR51	0.001 ***	0.000	0.001 ***	0.001 ***	0.002 ***
AT22	0.001 ***	0.002 ***	0.003 ***	0.001 ***	0.002 ***	FR52	0.002 ***	0.000 ***	0.002 ***	0.001 ***	0.004 ***
AT31	0.005 ***	0.001 ***	0.006 ***	0.004 ***	0.008 ***	FR53	-0.005 ***	0.001 ***	-0.004 ***	-0.003 ***	-0.007 ***
AT32	-0.013 ***	0.001 ***	-0.013 ***	-0.017 ***	-0.031 ***	FR61	0.001 ***	0.000 **	0.001 ***	0.000 ***	0.001 ***
AT33	0.003 ***	0.001 ***	0.004 ***	0.002 ***	0.005 ***	FR62	-0.003 ***	0.001 ***	-0.002 ***	-0.002 ***	-0.004 ***
AT34	0.002 ***	0.002 ***	0.005 ***	0.001 ***	0.004 ***	FR63	-0.009 ***	0.000	-0.008 ***	-0.004 ***	-0.013 ***
BE10	-0.010 ***	0.000 ***	-0.010 ***	-0.016 ***	-0.026 ***	FR71	0.000	0.001 ***	0.001 ***	0.000	0.000
BE21	-0.013 ***	0.001 ***	-0.013 ***	-0.017 ***	-0.031 ***	FR72	-0.007 ***	0.001 ***	-0.007 ***	-0.003 ***	-0.010 ***
BE22	-0.002 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.004 ***	FR81	0.001 ***	0.001 ***	0.001 ***	0.000 ***	0.001 ***
BE23	-0.001 ***	0.000	-0.001 ***	-0.001 ***	-0.002 ***	FR82	0.002 ***	0.000 ***	0.003 ***	0.002 ***	0.005 ***
BE24	-0.001 ***	0.000 ***	-0.002 ***	-0.001 ***	-0.002 ***	FR83	0.020 ***	-0.001 ***	0.020 ***	0.009 ***	0.030 ***
BE25	-0.003 ***	0.000 ***	-0.004 ***	-0.004 ***	-0.008 ***	ITC1	-0.002 ***	-0.005 ***	-0.007 ***	-0.004 ***	-0.006 ***
BE31	-0.012 ***	0.001 ***	-0.011 ***	-0.007 ***	-0.019 ***	ITC2	-0.011 ***	-0.004 ***	-0.015 ***	-0.002 ***	-0.013 ***
BE32	-0.006 ***	-0.001 ***	-0.007 ***	-0.005 ***	-0.011 ***	ITC3	0.000 **	-0.005 ***	-0.005 ***	0.000 **	0.000 **
BE33	-0.007 ***	0.000 ***	-0.007 ***	-0.005 ***	-0.012 ***	ITC4	-0.012 ***	-0.004 ***	-0.016 ***	-0.004 ***	-0.056 ***
BE34	-0.011 ***	-0.001 ***	-0.012 ***	-0.004 ***	-0.015 ***	ITD1	-0.006 ***	-0.004 ***	-0.010 ***	-0.002 ***	-0.008 ***
BE35	-0.009 ***	-0.001 ***	-0.010 ***	-0.004 ***	-0.013 ***	ITD2	-0.012 ***	-0.003 ***	-0.015 ***	-0.003 ***	-0.015 ***
DE10	0.008 ***	-0.002 ***	0.005 ***	0.010 ***	0.018 ***	ITD3	0.001 ***	-0.004 ***	-0.003 ***	0.002 ***	0.003 ***
DE20	0.008 ***	-0.001 ***	0.007 ***	0.013 ***	0.021 ***	ITD4	-0.003 ***	-0.003 ***	-0.007 ***	-0.002 ***	-0.005 ***
DE30	0.003 ***	-0.001 ***	0.002 ***	0.002 ***	0.006 ***	ITD5	-0.003 ***	-0.004 ***	-0.007 ***	-0.006 ***	-0.009 ***
DE40	0.008 ***	0.002 ***	0.010 ***	0.004 ***	0.012 ***	ITE1	0.001 ***	-0.004 ***	-0.003 ***	0.001 ***	0.002 ***
DE50	0.015 ***	-0.002 ***	0.013 ***	0.007 ***	0.022 ***	ITE2	-0.005 ***	-0.004 ***	-0.009 ***	-0.002 ***	-0.007 ***
DE60	0.007 ***	-0.003 ***	0.005 ***	0.005 ***	0.013 ***	ITE3	0.007 ***	-0.004 ***	0.003 ***	0.004 ***	0.011 ***
DE70	0.006 ***	-0.002 ***	0.004 ***	0.007 ***	0.014 ***	ITE4	-0.006 ***	-0.004 ***	-0.010 ***	-0.014 ***	-0.020 ***
DE80	-0.005 ***	0.001 ***	-0.004 ***	-0.002 ***	-0.007 ***	ITF1	-0.002 ***	-0.003 ***	-0.006 ***	-0.001 ***	-0.004 ***
DE90	0.007 ***	-0.002 ***	0.005 ***	0.007 ***	0.014 ***	ITF2	-0.012 ***	-0.004 ***	-0.016 ***	-0.001 ***	-0.013 ***
DEA0	0.011 ***	-0.002 ***	0.009 ***	0.026 ***	0.037 ***	ITF3	-0.001 ***	-0.004 ***	-0.005 ***	-0.001 ***	-0.002 ***
DEB0	0.003 ***	-0.001 ***	0.001 ***	0.002 ***	0.005 ***	ITF4	-0.003 ***	-0.004 ***	-0.006 ***	-0.004 ***	-0.006 ***
DEC0	0.016 ***	0.000 ***	0.016 ***	0.006 ***	0.022 ***	ITF5	-0.001 ***	-0.004 ***	-0.005 ***	0.000 ***	-0.002 ***
DED0	0.011 ***	0.001 ***	0.012 ***	0.006 ***	0.017 ***	ITF6	0.001 ***	-0.005 ***	-0.004 ***	0.001 ***	0.002 ***
DEE0	0.006 ***	0.002 ***	0.008 ***	0.003 ***	0.008 ***	ITG1	0.000 ***	-0.005 ***	-0.005 ***	0.001 ***	0.001 ***
DEF0	0.005 ***	-0.003 ***	0.002 ***	0.003 ***	0.008 ***	ITG2	-0.013 ***	-0.004 ***	-0.016 ***	-0.012 ***	-0.025 ***
DEG0	0.002 ***	0.001 ***	0.003 ***	0.001 ***	0.003 ***	NL11	0.004 ***	0.002 ***	0.007 ***	0.003 ***	0.007 ***
ES11	-0.007 ***	-0.001 ***	-0.008 ***	-0.007 ***	-0.014 ***	NL12	-0.003 ***	-0.002 ***	-0.005 ***	0.002 ***	-0.005 ***
ES12	-0.003 ***	-0.002 ***	-0.005 ***	-0.002 ***	-0.005 ***	NL13	0.001 ***	-0.003 ***	-0.002 ***	0.000 ***	0.002 ***
ES13	-0.006 ***	-0.002 ***	-0.008 ***	-0.002 ***	-0.008 ***	NL21	-0.001 ***	-0.002 ***	-0.002 ***	0.000 ***	-0.001 ***
ES21	-0.008 ***	0.005 ***	-0.003 ***	-0.003 ***	-0.011 ***	NL22	0.004 ***	-0.001 ***	0.002 ***	0.003 ***	0.007 ***
ES22	-0.006 ***	0.001 ***	-0.005 ***	-0.003 ***	-0.009 ***	NL23	0.009 ***	0.000 ***	0.009 ***	0.003 ***	0.013 ***
ES23	-0.004 ***	0.000 ***	-0.005 ***	-0.001 ***	-0.005 ***	NL31	-0.001 ***	-0.001 ***	-0.002 ***	-0.001 ***	-0.001 ***
ES24	-0.013 ***	0.000 ***	-0.013 ***	-0.009 ***	-0.022 ***	NL32	0.015 ***	-0.001 ***	0.014 ***	0.020 ***	0.035 ***
ES30	-0.007 ***	-0.002 ***	-0.009 ***	-0.027 ***	-0.035 ***	NL33	0.012 ***	-0.002 ***	0.010 ***	0.015 ***	0.026 ***
ES41	-0.006 ***	-0.001 ***	-0.007 ***	-0.005 ***	-0.011 ***	NL34	-0.002 ***	-0.002 ***	-0.004 ***	-0.001 ***	-0.003 ***
ES42	-0.011 ***	0.000 ***	-0.011 ***	-0.008 ***	-0.019 ***	NL41	0.009 ***	-0.001 ***	0.008 ***	0.010 ***	0.018 ***
ES43	-0.005 ***	0.000 ***	-0.005 ***	-0.003 ***	-0.008 ***	NL42	0.005 ***	-0.002 ***	0.003 ***	0.004 ***	0.009 ***
ES51	-0.009 ***	-0.001 ***	-0.010 ***	-0.003 ***	-0.012 ***	PT11	-0.019 ***	-0.003 ***	-0.022 ***	-0.017 ***	-0.036 ***
ES52	-0.017 ***	0.000 **	-0.018 ***	-0.028 ***	-0.046 ***	PT15	-0.010 ***	-0.006 ***	-0.016 ***	-0.006 ***	-0.016 ***
ES53	-0.025 ***	-0.002 ***	-0.027 ***	-0.021 ***	-0.046 ***	PT16	-0.014 ***	-0.003 ***	-0.017 ***	-0.011 ***	-0.025 ***
ES61	-0.011 ***	0.001 ***	-0.010 ***	-0.002 ***	-0.014 ***	PT17	0.002 ***	-0.004 ***	-0.002 ***	0.002 ***	0.004 ***
ES62	-0.012 ***	-0.002 ***	-0.015 ***	-0.008 ***	-0.020 ***	PT18	0.002 ***	-0.005 ***	-0.003 ***	0.001 ***	0.003 ***
ES70	-0.012 ***	-0.002 ***	-0.014 ***	-0.013 ***	-0.025 ***	SE11	0.008 ***	0.001 ***	0.009 ***	0.011 ***	0.019 ***
FR10	0.011 ***	0.000 ***	0.011 ***	0.038 ***	0.048 ***	SE12	-0.001 ***	0.000 **	-0.001 **	0.000 ***	-0.001 ***
FR21	-0.006 ***	-0.001 ***	-0.007 ***	-0.003 ***	-0.009 ***	SE21	0.006 ***	-0.002 ***	0.004 ***	0.003 ***	0.009 ***
FR22	-0.008 ***	0.000 ***	-0.009 ***	-0.004 ***	-0.012 ***	SE22	0.008 ***	-0.002 ***	0.006 ***	0.006 ***	0.014 ***
FR23	-0.005 ***	0.002 ***	-0.004 ***	-0.003 ***	-0.008 ***	SE23	0.007 ***	-0.001 ***	0.005 ***	0.006 ***	0.013 ***
FR24	-0.003 ***	0.000 ***	-0.003 ***	-0.002 ***	-0.004 ***	SE31	0.010 ***	-0.003 ***	0.007 ***	0.006 ***	0.016 ***
FR25	-0.007 ***	0.001 ***	-0.006 ***	-0.003 ***	-0.010 ***	SE32	0.000	-0.001 ***	0.000	0.000	0.001
FR26	0.004 ***	-0.001 ***	0.003 ***	0.003 ***	0.007 ***	SE33	-0.006 ***	0.000	-0.006 ***	-0.002 ***	-0.008 ***
FR30	0.000 **	-0.001 ***	-0.001 ***	0.000 **	0.000 **						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

RSFB Services						RSFB Services					
Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered	Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.003 ***	0.002 ***	0.005 ***	0.001 ***	0.004 ***	FR41	-0.016 ***	0.000 ***	-0.016 ***	-0.011 ***	-0.027 ***
AT12	0.008 ***	0.001 ***	0.009 ***	0.006 ***	0.014 ***	FR42	-0.018 ***	0.001 ***	-0.017 ***	-0.011 ***	-0.029 ***
AT13	-0.002 ***	-0.001 ***	-0.003 ***	-0.003 ***	-0.005 ***	FR43	-0.010 ***	-0.001 ***	-0.011 ***	-0.006 ***	-0.016 ***
AT21	-0.003 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.004 ***	FR51	-0.010 ***	0.001 ***	-0.009 ***	-0.008 ***	-0.019 ***
AT22	0.001 ***	0.001 ***	0.002 ***	0.001 ***	0.002 ***	FR52	-0.011 ***	0.001 ***	-0.010 ***	-0.008 ***	-0.019 ***
AT31	0.002 ***	0.001 ***	0.003 ***	0.001 ***	0.003 ***	FR53	-0.011 ***	0.001 ***	-0.010 ***	-0.007 ***	-0.017 ***
AT32	-0.006 ***	0.001 ***	-0.005 ***	-0.003 ***	-0.009 ***	FR61	-0.011 ***	0.001 ***	-0.010 ***	-0.008 ***	-0.019 ***
AT33	-0.009 ***	0.001 ***	-0.007 ***	-0.005 ***	-0.014 ***	FR62	-0.010 ***	0.001 ***	-0.009 ***	-0.007 ***	-0.016 ***
AT34	-0.004 ***	0.002 ***	-0.002 ***	-0.002 ***	-0.005 ***	FR63	-0.015 ***	0.000 ***	-0.016 ***	-0.007 ***	-0.022 ***
BE10	-0.007 ***	-0.002 ***	-0.009 ***	-0.009 ***	-0.017 ***	FR71	-0.010 ***	0.001 ***	-0.008 ***	-0.010 ***	-0.020 ***
BE21	-0.009 ***	-0.001 ***	-0.011 ***	-0.010 ***	-0.019 ***	FR72	-0.007 ***	0.000 *	-0.007 ***	-0.003 ***	-0.010 ***
BE22	-0.014 ***	-0.001 ***	-0.015 ***	-0.007 ***	-0.020 ***	FR81	-0.011 ***	0.001 ***	-0.010 ***	-0.007 ***	-0.018 ***
BE23	-0.013 ***	-0.001 ***	-0.013 ***	-0.010 ***	-0.022 ***	FR82	-0.014 ***	0.002 ***	-0.012 ***	-0.012 ***	-0.026 ***
BE24	-0.012 ***	-0.001 ***	-0.012 ***	-0.007 ***	-0.019 ***	FR83	-0.024 ***	0.004 ***	-0.020 ***	-0.010 ***	-0.034 ***
BE25	-0.011 ***	-0.001 ***	-0.012 ***	-0.018 ***	-0.018 ***	ITC1	-0.017 ***	-0.004 ***	-0.021 ***	-0.012 ***	-0.031 ***
BE31	-0.007 ***	-0.002 ***	-0.009 ***	-0.003 ***	-0.010 ***	ITC2	-0.010 ***	-0.004 ***	-0.014 ***	-0.001 ***	-0.011 ***
BE32	-0.019 ***	-0.001 ***	-0.021 ***	-0.013 ***	-0.032 ***	ITC3	-0.011 ***	-0.005 ***	-0.016 ***	-0.003 ***	-0.014 ***
BE33	-0.017 ***	-0.001 ***	-0.018 ***	-0.012 ***	-0.029 ***	ITC4	-0.008 ***	-0.005 ***	-0.012 ***	-0.026 ***	-0.034 ***
BE34	-0.020 ***	-0.002 ***	-0.022 ***	-0.006 ***	-0.025 ***	ITD1	-0.015 ***	-0.005 ***	-0.020 ***	-0.002 ***	-0.017 ***
BE35	-0.018 ***	-0.002 ***	-0.021 ***	-0.008 ***	-0.027 ***	ITD2	-0.009 ***	-0.005 ***	-0.014 ***	-0.001 ***	-0.011 ***
DE10	-0.020 ***	0.000 ***	-0.020 ***	-0.029 ***	-0.049 ***	ITD3	-0.015 ***	-0.004 ***	-0.019 ***	-0.021 ***	-0.035 ***
DE20	-0.018 ***	0.000 ***	-0.017 ***	-0.034 ***	-0.051 ***	ITD4	-0.010 ***	-0.004 ***	-0.015 ***	-0.003 ***	-0.013 ***
DE30	-0.014 ***	-0.001 ***	-0.015 ***	-0.011 ***	-0.025 ***	ITD5	-0.013 ***	-0.004 ***	-0.017 ***	-0.016 ***	-0.028 ***
DE40	0.002 ***	0.001 ***	0.003 ***	0.001 ***	0.003 ***	ITE1	-0.011 ***	-0.004 ***	-0.015 ***	-0.011 ***	-0.022 ***
DE50	-0.025 ***	0.000 *	-0.025 ***	-0.013 ***	-0.037 ***	ITE2	-0.012 ***	-0.004 ***	-0.016 ***	-0.002 ***	-0.014 ***
DE60	-0.022 ***	-0.001 ***	-0.024 ***	-0.019 ***	-0.041 ***	ITE3	-0.013 ***	-0.004 ***	-0.017 ***	-0.002 ***	-0.017 ***
DE70	-0.019 ***	-0.001 ***	-0.020 ***	-0.025 ***	-0.044 ***	ITE4	-0.007 ***	-0.005 ***	-0.012 ***	-0.013 ***	-0.020 ***
DE80	-0.009 ***	0.000 ***	-0.009 ***	-0.004 ***	-0.013 ***	ITF1	-0.015 ***	-0.004 ***	-0.019 ***	-0.004 ***	-0.019 ***
DE90	-0.019 ***	0.000 ***	-0.019 ***	-0.022 ***	-0.041 ***	ITF2	-0.018 ***	-0.004 ***	-0.022 ***	-0.001 ***	-0.019 ***
DEA0	-0.021 ***	0.000 ***	-0.020 ***	-0.044 ***	-0.065 ***	ITF3	-0.010 ***	-0.004 ***	-0.014 ***	-0.012 ***	-0.022 ***
DEB0	-0.013 ***	-0.001 ***	-0.014 ***	-0.012 ***	-0.025 ***	ITF4	-0.011 ***	-0.004 ***	-0.015 ***	-0.009 ***	-0.020 ***
DEC0	-0.027 ***	0.002 ***	-0.025 ***	-0.014 ***	-0.041 ***	ITF5	-0.019 ***	-0.004 ***	-0.023 ***	-0.002 ***	-0.021 ***
DED0	-0.012 ***	0.002 ***	-0.010 ***	-0.009 ***	-0.021 ***	ITF6	-0.016 ***	-0.004 ***	-0.020 ***	-0.006 ***	-0.022 ***
DEE0	-0.014 ***	0.002 ***	-0.012 ***	-0.008 ***	-0.022 ***	ITG1	-0.007 ***	-0.004 ***	-0.011 ***	-0.003 ***	-0.009 ***
DEF0	-0.028 ***	-0.001 ***	-0.029 ***	-0.019 ***	-0.048 ***	ITG2	-0.015 ***	-0.005 ***	-0.020 ***	-0.004 ***	-0.019 ***
DEG0	-0.013 ***	0.000 ***	-0.012 ***	-0.006 ***	-0.019 ***	NL11	-0.022 ***	0.002 ***	-0.020 ***	-0.014 ***	-0.036 ***
ES11	-0.011 ***	-0.002 ***	-0.014 ***	-0.011 ***	-0.022 ***	NL12	-0.015 ***	-0.002 ***	-0.017 ***	-0.009 ***	-0.024 ***
ES12	-0.005 ***	-0.003 ***	-0.009 ***	-0.003 ***	-0.009 ***	NL13	-0.009 ***	-0.003 ***	-0.012 ***	-0.005 ***	-0.014 ***
ES13	-0.016 ***	-0.003 ***	-0.019 ***	-0.006 ***	-0.022 ***	NL21	-0.007 ***	-0.002 ***	-0.009 ***	-0.006 ***	-0.013 ***
ES21	0.005 ***	0.001 ***	0.005 ***	0.004 ***	0.008 ***	NL22	-0.009 ***	-0.001 ***	-0.010 ***	-0.009 ***	-0.019 ***
ES22	0.001 ***	-0.002 ***	-0.001 ***	0.001 ***	0.002 ***	NL23	0.012 ***	-0.001 ***	0.011 ***	0.004 ***	0.016 ***
ES23	-0.007 ***	-0.003 ***	-0.009 ***	-0.002 ***	-0.008 ***	NL31	0.001 ***	-0.002 ***	0.000 ***	0.001 ***	0.003 ***
ES24	0.003 ***	-0.003 ***	-0.001 ***	0.002 ***	0.004 ***	NL32	0.008 ***	-0.001 ***	0.007 ***	0.011 ***	0.019 ***
ES30	0.003 ***	-0.005 ***	-0.001 ***	0.004 ***	0.007 ***	NL33	-0.002 ***	0.000 ***	-0.003 ***	-0.003 ***	-0.005 ***
ES41	-0.014 ***	-0.003 ***	-0.017 ***	-0.006 ***	-0.020 ***	NL34	-0.007 ***	-0.002 ***	-0.009 ***	-0.002 ***	-0.010 ***
ES42	-0.002 ***	-0.002 ***	-0.004 ***	-0.001 ***	-0.003 ***	NL41	-0.004 ***	-0.001 ***	-0.005 ***	-0.005 ***	-0.010 ***
ES43	0.005 ***	-0.002 ***	0.003 ***	0.002 ***	0.007 ***	NL42	-0.015 ***	-0.001 ***	-0.016 ***	-0.009 ***	-0.025 ***
ES51	0.004 ***	-0.003 ***	0.001 ***	0.002 ***	0.006 ***	PT11	-0.012 ***	-0.006 ***	-0.018 ***	-0.008 ***	-0.020 ***
ES52	-0.005 ***	-0.004 ***	-0.010 ***	-0.003 ***	-0.009 ***	PT15	-0.021 ***	-0.006 ***	-0.027 ***	-0.007 ***	-0.028 ***
ES53	0.002 ***	-0.007 ***	-0.005 ***	0.001 ***	0.003 ***	PT16	-0.006 ***	-0.006 ***	-0.011 ***	-0.003 ***	-0.009 ***
ES61	-0.009 ***	0.000 ***	-0.010 ***	-0.002 ***	-0.011 ***	PT17	-0.009 ***	-0.004 ***	-0.013 ***	-0.009 ***	-0.018 ***
ES62	-0.012 ***	-0.003 ***	-0.015 ***	-0.012 ***	-0.024 ***	PT18	-0.014 ***	-0.005 ***	-0.019 ***	-0.005 ***	-0.019 ***
ES70	-0.002 ***	-0.005 ***	-0.007 ***	-0.001 ***	-0.003 ***	SE11	-0.008 ***	0.001 ***	-0.007 ***	-0.014 ***	-0.022 ***
FR10	-0.002 ***	0.001 ***	-0.001 ***	-0.006 ***	-0.008 ***	SE12	-0.015 ***	-0.001 ***	-0.016 ***	-0.011 ***	-0.026 ***
FR21	-0.018 ***	0.000 ***	-0.019 ***	-0.010 ***	-0.028 ***	SE21	-0.021 ***	-0.002 ***	-0.022 ***	-0.014 ***	-0.035 ***
FR22	-0.010 ***	-0.001 ***	-0.011 ***	-0.006 ***	-0.017 ***	SE22	-0.015 ***	-0.002 ***	-0.017 ***	-0.012 ***	-0.027 ***
FR23	-0.012 ***	0.001 ***	-0.011 ***	-0.007 ***	-0.019 ***	SE23	-0.012 ***	-0.002 ***	-0.014 ***	-0.012 ***	-0.025 ***
FR24	-0.012 ***	0.000 ***	-0.012 ***	-0.009 ***	-0.021 ***	SE31	-0.026 ***	-0.002 ***	-0.028 ***	-0.016 ***	-0.043 ***
FR25	-0.010 ***	0.000 ***	-0.009 ***	-0.005 ***	-0.015 ***	SE32	-0.022 ***	-0.001 ***	-0.022 ***	-0.007 ***	-0.029 ***
FR26	-0.013 ***	0.000 ***	-0.013 ***	-0.008 ***	-0.021 ***	SE33	-0.020 ***	-0.002 ***	-0.022 ***	-0.010 ***	-0.031 ***
FR30	-0.011 ***	0.000 ***	-0.011 ***	-0.010 ***	-0.021 ***						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

NM Services						NM Services					
Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered	Country-Region	Direct	Indirect-received	Total-received	Indirect-offered	Total-offered
AT11	0.000	0.002 ***	0.002 ***	0.000	0.000	FR41	-0.007 ***	-0.001 ***	-0.008 ***	-0.002 ***	-0.009 ***
AT12	0.006 ***	0.001 ***	0.007 ***	0.001 ***	0.007 ***	FR42	-0.005 ***	-0.001 ***	-0.006 ***	-0.001 ***	-0.006 ***
AT13	-0.005 ***	0.000	-0.005 ***	-0.003 ***	-0.008 ***	FR43	-0.001 ***	-0.002 ***	-0.002 ***	0.000 ***	-0.001 ***
AT21	-0.001 ***	0.000 ***	-0.001 **	0.000 ***	-0.001 ***	FR51	0.002 ***	-0.001 ***	0.001 ***	0.001 ***	0.002 ***
AT22	-0.005 ***	0.001 ***	-0.004 ***	-0.001 ***	-0.006 ***	FR52	-0.007 ***	0.000 ***	-0.007 ***	-0.002 ***	-0.009 ***
AT31	-0.001 ***	0.001 ***	0.001 ***	0.000 ***	-0.001 ***	FR53	0.001 ***	0.000 ***	0.001 ***	0.000 ***	0.001 ***
AT32	-0.003 ***	0.000 **	-0.003 ***	-0.001 ***	-0.004 ***	FR61	-0.003 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.004 ***
AT33	0.004 ***	0.000 ***	0.004 ***	0.001 ***	0.005 ***	FR62	0.000 ***	0.000 ***	0.000 **	0.000 ***	0.001 ***
AT34	-0.002 ***	0.001 ***	0.000 ***	0.000 ***	-0.002 ***	FR63	0.001 ***	-0.002 ***	-0.001 ***	0.000 ***	0.001 ***
BE10	0.001 *	-0.002 ***	-0.001 ***	0.000 *	0.001 *	FR71	0.000 *	0.000 ***	0.000 ***	0.000 *	0.000 *
BE21	0.000 ***	-0.002 ***	-0.002 ***	0.000 ***	-0.001 ***	FR72	-0.003 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.003 ***
BE22	0.002 ***	-0.001 ***	0.001 ***	0.000 ***	0.003 ***	FR81	0.007 ***	0.000 ***	0.007 ***	0.002 ***	0.009 ***
BE23	-0.002 ***	-0.001 ***	-0.004 ***	0.000 ***	-0.003 ***	FR82	-0.005 ***	0.000 ***	-0.006 ***	-0.002 ***	-0.007 ***
BE24	-0.005 ***	-0.001 ***	-0.007 ***	-0.001 ***	-0.006 ***	FR83	0.007 ***	0.001 ***	0.008 ***	0.002 ***	0.009 ***
BE25	-0.002 ***	-0.003 ***	-0.004 ***	-0.003 ***	-0.004 ***	ITC1	-0.008 ***	-0.005 ***	-0.012 ***	-0.002 ***	-0.012 ***
BE31	-0.005 ***	-0.001 ***	-0.006 ***	-0.001 ***	-0.005 ***	ITC2	-0.001 ***	-0.005 ***	-0.006 ***	0.000 ***	-0.001 ***
BE32	0.003 ***	-0.002 ***	0.001 ***	0.001 ***	0.004 ***	ITC3	-0.009 ***	-0.005 ***	-0.013 ***	-0.001 ***	-0.009 ***
BE33	0.002 ***	-0.002 ***	0.001 ***	0.001 ***	0.003 ***	ITC4	-0.007 ***	-0.005 ***	-0.011 ***	-0.009 ***	-0.015 ***
BE34	0.005 ***	-0.003 ***	0.002 ***	0.001 ***	0.005 ***	ITD1	0.001 ***	-0.004 ***	-0.003 ***	0.000 ***	0.001 ***
BE35	0.002 ***	-0.002 ***	0.000	0.000 ***	0.003 ***	ITD2	-0.004 ***	-0.004 ***	-0.008 ***	0.000 ***	-0.004 ***
DE10	-0.003 ***	-0.003 ***	-0.006 ***	-0.002 ***	-0.004 ***	ITD3	-0.003 ***	-0.004 ***	-0.008 ***	-0.001 ***	-0.005 ***
DE20	-0.004 ***	-0.002 ***	-0.006 ***	-0.002 ***	-0.007 ***	ITD4	-0.005 ***	-0.004 ***	-0.009 ***	-0.001 ***	-0.005 ***
DE30	0.000 ***	-0.002 ***	-0.002 ***	0.000 ***	0.000 ***	ITD5	-0.003 ***	-0.004 ***	-0.007 ***	-0.001 ***	-0.004 ***
DE40	0.004 ***	0.001 ***	0.005 ***	0.001 ***	0.005 ***	ITE1	-0.006 ***	-0.004 ***	-0.010 ***	-0.002 ***	-0.007 ***
DE50	-0.003 ***	-0.003 ***	-0.006 ***	-0.001 ***	-0.004 ***	ITE2	-0.005 ***	-0.004 ***	-0.009 ***	0.000 ***	-0.005 ***
DE60	-0.009 ***	-0.004 ***	-0.013 ***	-0.003 ***	-0.012 ***	ITE3	-0.001 ***	-0.004 ***	-0.005 ***	0.000 ***	-0.001 ***
DE70	-0.003 ***	-0.003 ***	-0.006 ***	-0.001 ***	-0.004 ***	ITE4	-0.011 ***	-0.004 ***	-0.015 ***	-0.010 ***	-0.021 ***
DE80	0.006 ***	-0.001 ***	0.005 ***	0.002 ***	0.008 ***	ITF1	-0.013 ***	-0.004 ***	-0.016 ***	-0.001 ***	-0.014 ***
DE90	-0.004 ***	-0.002 ***	-0.006 ***	-0.003 ***	-0.007 ***	ITF2	-0.006 ***	-0.005 ***	-0.010 ***	0.000 ***	-0.006 ***
DEA0	-0.001 ***	-0.003 ***	-0.004 ***	-0.001 ***	-0.002 ***	ITF3	-0.005 ***	-0.004 ***	-0.009 ***	-0.002 ***	-0.007 ***
DEB0	-0.005 ***	-0.002 ***	-0.007 ***	-0.002 ***	-0.007 ***	ITF4	-0.009 ***	-0.004 ***	-0.013 ***	-0.002 ***	-0.011 ***
DEC0	-0.001 ***	-0.002 ***	-0.003 ***	0.000 ***	-0.002 ***	ITF5	-0.004 ***	-0.004 ***	-0.008 ***	0.000 ***	-0.004 ***
DED0	0.004 ***	0.000 ***	0.004 ***	0.002 ***	0.005 ***	ITF6	-0.011 ***	-0.004 ***	-0.015 ***	-0.004 ***	-0.015 ***
DEE0	0.005 ***	0.000 ***	0.005 ***	0.002 ***	0.007 ***	ITG1	-0.008 ***	-0.004 ***	-0.013 ***	-0.003 ***	-0.011 ***
DEF0	0.002 ***	-0.004 ***	-0.002 ***	0.001 ***	0.003 ***	ITG2	-0.006 ***	-0.005 ***	-0.011 ***	-0.001 ***	-0.008 ***
DEG0	0.007 ***	-0.001 ***	0.006 ***	0.002 ***	0.009 ***	NL11	-0.007 ***	0.000 *	-0.006 ***	-0.002 ***	-0.008 ***
ES11	-0.005 ***	-0.002 ***	-0.007 ***	-0.001 ***	-0.006 ***	NL12	-0.008 ***	-0.003 ***	-0.010 ***	-0.002 ***	-0.009 ***
ES12	0.000 *	-0.003 ***	-0.003 ***	0.000 *	-0.001 *	NL13	-0.008 ***	-0.003 ***	-0.011 ***	-0.002 ***	-0.009 ***
ES13	-0.002 ***	-0.003 ***	-0.005 ***	0.000 ***	-0.002 ***	NL21	-0.006 ***	-0.002 ***	-0.008 ***	-0.002 ***	-0.007 ***
ES21	-0.010 ***	0.004 ***	-0.006 ***	-0.001 ***	-0.011 ***	NL22	-0.004 ***	-0.002 ***	-0.006 ***	-0.002 ***	-0.005 ***
ES22	-0.006 ***	0.000 *	-0.006 ***	-0.001 ***	-0.007 ***	NL23	0.001 ***	0.000 ***	0.001 ***	0.000 ***	0.002 ***
ES23	-0.011 ***	-0.001 ***	-0.012 ***	-0.001 ***	-0.012 ***	NL31	-0.008 ***	-0.001 ***	-0.009 ***	-0.003 ***	-0.011 ***
ES24	-0.007 ***	-0.001 ***	-0.008 ***	-0.001 ***	-0.008 ***	NL32	-0.007 ***	0.000 ***	-0.006 ***	-0.004 ***	-0.010 ***
ES30	-0.002 ***	-0.002 ***	-0.005 ***	-0.002 ***	-0.004 ***	NL33	-0.008 ***	-0.001 ***	-0.008 ***	-0.004 ***	-0.012 ***
ES41	0.000 **	-0.002 ***	-0.002 ***	0.000 **	0.000 **	NL34	-0.011 ***	-0.002 ***	-0.014 ***	-0.001 ***	-0.013 ***
ES42	0.002 ***	-0.001 ***	0.001 ***	0.000 ***	0.002 ***	NL41	-0.007 ***	-0.001 ***	-0.008 ***	-0.003 ***	-0.011 ***
ES43	-0.002 ***	-0.001 ***	-0.003 ***	0.000 ***	-0.002 ***	NL42	-0.002 ***	-0.002 ***	-0.004 ***	-0.001 ***	-0.002 ***
ES51	-0.010 ***	-0.001 ***	-0.011 ***	-0.004 ***	-0.014 ***	PT11	-0.017 ***	-0.005 ***	-0.021 ***	-0.007 ***	-0.023 ***
ES52	0.001 ***	-0.002 ***	-0.002 ***	0.000 ***	0.001 ***	PT15	-0.014 ***	-0.006 ***	-0.020 ***	-0.003 ***	-0.017 ***
ES53	-0.008 ***	-0.005 ***	-0.012 ***	-0.002 ***	-0.010 ***	PT16	-0.015 ***	-0.004 ***	-0.019 ***	-0.005 ***	-0.020 ***
ES61	-0.004 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.004 ***	PT17	-0.016 ***	-0.002 ***	-0.019 ***	-0.006 ***	-0.022 ***
ES62	0.002 ***	-0.003 ***	-0.001 ***	0.000 ***	0.003 ***	PT18	-0.017 ***	-0.004 ***	-0.021 ***	-0.003 ***	-0.020 ***
ES70	0.000 ***	-0.004 ***	-0.004 ***	0.000 ***	0.000 ***	SE11	-0.016 ***	0.000 ***	-0.016 ***	-0.005 ***	-0.021 ***
FR10	-0.010 ***	0.001 ***	-0.009 ***	-0.008 ***	-0.017 ***	SE12	-0.012 ***	-0.002 ***	-0.014 ***	-0.005 ***	-0.017 ***
FR21	-0.005 ***	-0.002 ***	-0.007 ***	-0.001 ***	-0.006 ***	SE21	-0.008 ***	-0.004 ***	-0.012 ***	-0.002 ***	-0.010 ***
FR22	0.001 ***	-0.002 ***	-0.001 ***	0.000 ***	0.001 ***	SE22	-0.018 ***	-0.003 ***	-0.021 ***	-0.008 ***	-0.026 ***
FR23	0.000 **	0.000 ***	0.000	0.000 **	0.001 **	SE23	-0.016 ***	-0.002 ***	-0.017 ***	-0.017 ***	-0.032 ***
FR24	-0.006 ***	-0.001 ***	-0.007 ***	-0.002 ***	-0.008 ***	SE31	-0.006 ***	-0.003 ***	-0.010 ***	-0.002 ***	-0.008 ***
FR25	-0.003 ***	0.000 ***	-0.003 ***	-0.001 ***	-0.003 ***	SE32	-0.016 ***	-0.001 ***	-0.016 ***	-0.003 ***	-0.018 ***
FR26	-0.004 ***	-0.001 ***	-0.005 ***	-0.001 ***	-0.005 ***	SE33	-0.020 ***	-0.003 ***	-0.022 ***	-0.006 ***	-0.026 ***
FR30	0.002 ***	-0.001 ***	0.001 ***	0.001 ***	0.003 ***						

Note: *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix J. Cobb-Douglas model with country-specific elasticities

	Specification of the elasticity of capital deepening			
	Common ^(a)		Country-specific	
	Coef.	s.e.	Coef.	s.e.
<i>Coefficient of $\ln k$</i>				
<u>All countries</u>	0.407 ***	0.007		
Austria			0.513 ***	0.022
Belgium			0.567 ***	0.021
Germany			0.182 ***	0.017
Spain			0.335 ***	0.014
France			0.664 ***	0.018
Italy			0.485 ***	0.015
Netherlands			0.288 ***	0.021
Portugal			0.421 ***	0.027
Sweden			0.626 ***	0.023
<i>Autoregressive coefficient</i>				
ρ	0.406 ***	0.014	0.420 ***	0.014
Time trend	Yes		Yes	
Sector effects	Yes		Yes	
Country effects	Yes		Yes	
sigma	0.007		0.006	
R ²	0.791		0.672	
lnL	16128.7		16380.6	

Notes: (a) This model coincides with the SAR RE-Hicks neutral model in Table 2. *(**)(***) stands for statistical significance at 10%(5%)(1%)

Appendix K. Parameter estimates using alternative production functions.

	Cobb-Douglas						Translog		
	CRS ^(a)			VRS			CRS		
	Coef. ^(b)		s.e.	Coef.		s.e.	Coef. ^(b)		s.e.
<i>Production function</i>									
lnK	0.407 ***		0.007	0.196 ***		0.009	0.455 ***		0.008
lnL	<u>0.593</u>		-	0.440 ***		0.009	<u>0.545</u>		-
lnK ²							0.106 ***		0.004
lnL ²							<u>0.106</u>		
lnK·lnL							<u>-0.212</u>		
<i>Autoregressive coefficient</i>									
ρ	0.406 ***		0.014	0.344 ***		0.012	0.408 ***		0.013
<i>Scale elasticity</i>									
	1			0.636			1 ^(c)		
Capital share	0.407			0.308			0.455		
Labor share	<u>0.593</u>			0.692			<u>0.545</u>		
Time trend	Yes			Yes			Yes		
Sector effects	Yes			Yes			Yes		
Country effects	Yes			Yes			Yes		
sigma	0.007			0.006			0.006		
R ²	0.791			0.941			0.779		
lnL	16128.7			16552.2			16512.1		

Notes: (a) This model coincides with the SAR RE-Hicks neutral model in Table 2. (b) The underlined parameters have been calculated through the homogeneity conditions. (c) Elasticity evaluated at the sample mean. *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix L. SDM model. CRS vs VRS specifications.

	CRS ^(a)			VRS		
	Coef.	^(b)	s.e.	Coef.		s.e.
<i>Production function</i>						
lnK	0.397	***	0.008	0.184	***	0.010
lnL	<u>0.603</u>			0.478	***	0.009
W·lnK	0.076		0.019	0.165	***	0.019
W·lnL	<u>-0.076</u>			-0.229	***	0.021
<i>Autoregressive coefficient</i>						
ρ	0.386	***	0.016	0.392	***	0.015
<i>Spatial input-specific parameters</i>						
ϕ_K	0.229			0.237		
ϕ_L	<u>-0.229</u>			-0.042		
Time trend	Yes			Yes		
Sector effects	Yes			Yes		
Country effects	Yes			Yes		
sigma	0.007			0.006		
R ²	0.716			0.941		
LnL	16130.8			16552.2		

Notes: (a) This model coincides with the SDM RE-Hicks neutral model in Table 2. (b) The underlined parameters have been calculated applying homogeneity conditions. (b) Elasticity evaluated at the sample mean. *(**)(***) stands for statistical significance at 10%(5%)(1%).

Appendix M. Computation of output changes.

In our paper we conduct various counterfactual analyses to explore the output changes (productivity effects) attributable to changes in the trade network, TFP improvements due to digitalization, the collapse of the construction sector and the start of the financial crisis. All simulation exercises are carried out using a Hicks-neutral SAR specification of our model. As we are going to use different W matrices in our simulations, we employ the estimated coefficients of the SAR model that uses a time-varying W matrix, normalized with the row-sum of the intermediate in 2000 (see [Appendix E](#), Table a)).

From the SAR model in equation (6), we can express the logarithmic of output as:

$$\ln Y = \Omega(UK + UL + UT), \quad (J.1)$$

where Ω is the so-called global multiplier, which is a function of the spatial weighted matrix, W . As in [Liu and Sickles \(2021\)](#), UK and UL measure the output contribution of production factors, and UT the effect of initial technology state and technology growth. We hereafter assume that both capital and labor components in (J.1) are not influenced by the performed symmetric and asymmetric shocks. While the first simulation exercise involves changing the global multiplier due to a change in the spatial weighted matrix from 2000 to 2010, the other simulations rely on a change in the technology component UT . That is, to compute the output changes due to progress of the trade network, we use:

$$\Delta \ln Y = \Delta \Omega \cdot (UK_{2000} + UL_{2000} + UT_{2000}), \quad (J.2)$$

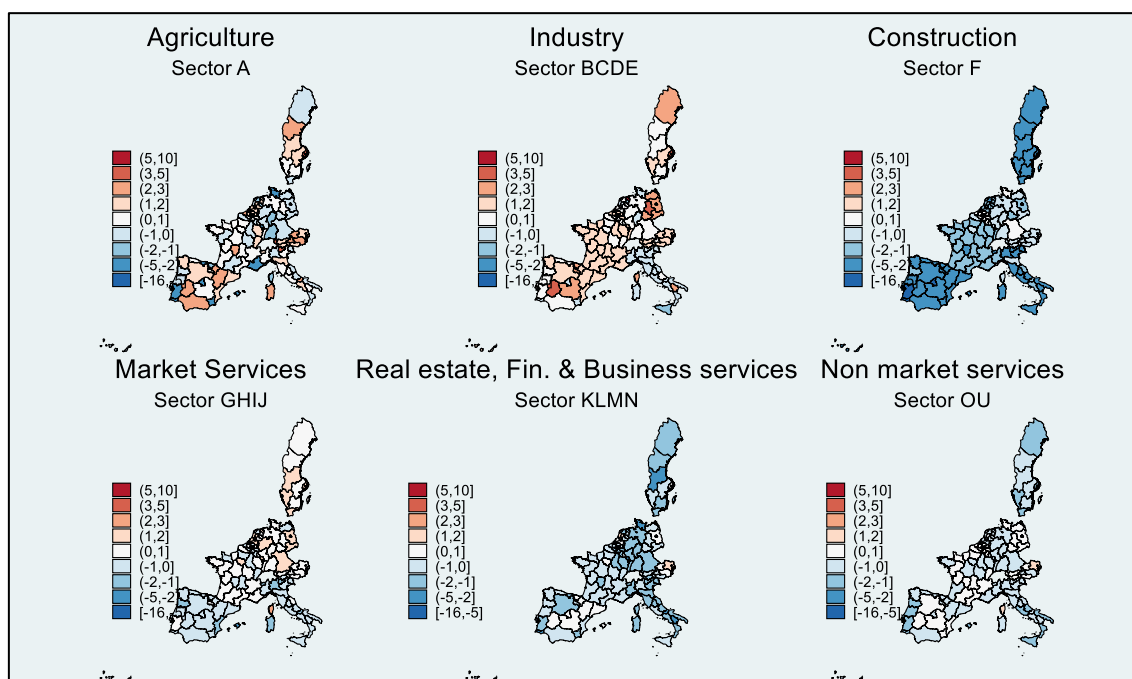
where $\Delta \Omega = \Omega(W_{2010}) - \Omega(W_{2000})$. In contrast, the change in Y resulting from TFP improvements due to digitalization, the collapse of the construction sector and the start of the financial crisis are computed as follows:

$$\Delta \ln Y = \Omega \cdot \Delta UT, \quad (J.3)$$

To prevent the selection of a specific annual W matrix potentially biasing our results, the simulations based on equation (J.3) are computed using the arithmetic mean of all spatial weighted matrices from 2000 to 2010. These simulations only differ in the change that we perform for the technology component UT . To compute the change in Y resulting from TFP improvements due to digitalization, we assume that $\Delta UT = 0.006$ in *Industry* and $\Delta UT = 0.003$ in *Market Services*. The output effects of the collapse of the construction sector are computed assuming that in this sector ΔUT is equal to -0.0697 in Austria, 0.0013 in Belgium, 0.022 in Germany, -0.1180 in Spain, -0.0426 in France, -0.0602 in Italy, -0.0802 in Netherlands, -0.0914 in Portugal, and -0.0283 in Sweden. The output effects of the start of the financial crisis are computed assuming that, in the *Real Estate, Financial & Business Services* sector, ΔUT is equal to -0.0129 in Austria, -0.0144 in Belgium, -0.0466 in Germany, -0.0124 in Spain, -0.0198 in France, -0.0216 in Italy, -0.0267 in Netherlands, -0.0005 in Portugal, and -0.1233 in Sweden. To simulate a symmetric shock in this sector we simply assume that $\Delta UT = -0.0284$.

For our simulation of the economic consequences of the Russia-Ukraine war, we simply assume that ΔUT in sector A is as follows: Netherlands -1.54%, Italy -1.40%, Belgium -1.22%, Austria -0.79%, France -1.19%, Spain -1.46%, Germany -0.94%, Portugal -1.44% and Sweden -0.68%. The ΔUT values used to approximate the initial shocks in the BCDE sector are as follows: Netherlands -0.26%, Italy -0.39%, Belgium -0.57%, Austria -0.64%, France -0.20%, Spain -0.20%, Germany -0.44%, Portugal -0.10% and Sweden -0.61%.

Appendix N. Estimated TFP growth using a non-spatial model. 1995-2014.



Note: Annual rate of growth in percentage. CSS model estimated using a RE estimator. Hicks neutral specification.