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Sectoral trade elasticities and consequences of embeddedness for the economic performance of the European regions

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Abstract:

This paper simultaneously estimates sectoral trade elasticities among European regions and the effect that the degree of embeddedness has on regional productivity. Our approach combines a production-based model with the proxy-variable method, while accounting for spatial spillover effects related to technology diffusion. We find evidence of heterogeneity in regional trade elasticities and show that productivity spillovers are positive and significant. Additionally, our results reveal that embeddedness has a positive and significant effect, supporting the existence of agglomeration and proximity externalities during the period considered. These findings offer valuable insights for policymakers, providing the basis for designing regional development and sectoral strategies. In a globalized world, where production is more fragmented and regions are increasingly becoming more specialized and interconnected, understanding regional trade dynamics and responses is essential for boosting regional resilience.

JEL codes: F14, O47, C68

Keywords: Total factor productivity, trade elasticities, trade linkages, embeddedness, regional economies.

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1. Introduction

Heterogeneity in the economic performances of territories becomes more pronounced as we analyse smaller geographical scales. This applies to most economic performance variables, such as gross domestic product (GDP) per capita or for disposable income per capita (McCann, 2020), as well as for trade openness and foreign dependency (Kitsos et al. 2023). Smaller economies tend to exhibit greater specialization in production, leading to a concentration in specific sectors with different value-added and productivity potential. This specialization also makes them more reliant on external resources, with the result that when analysing trade dynamics at regional instead of country level, we observe an increasingly fragmented global production landscape (Bolea et al. 2022).

Due to the limited availability of detailed trade data between regions, most analyses explaining trade are carried out at country level (Santamaria et al. 2023). However, regional economies within countries present more extreme cases than national economies. Regions that are very open to trade tend to be more vulnerable to external negative shocks, but at the same time they can benefit from access to cheaper production inputs and positive knowledge spillovers. In contrast, regions that are less open to trade are less exposed to global crises but also receive fewer spillovers, are less connected to other sources of inputs, and are at a greater risk of lock-in due to their higher dependence on local industries. In their analysis of the impact of technical change and catch-up on economic development in European regions, Carrascal-Incera et al. (2025) show that significant economic effects can be overlooked if inter-regional and inter-sectoral spillovers via the commercial networks are neglected.

Recent examples of this regional heterogeneity in response to external shocks highlight the importance of carrying out subnational analyses. Analysing the impact of Brexit on regions using EUREGIO data, Los et al. (2017) find that UK regions voting in favour of leaving the EU in the 2016 Brexit referendum were those with a higher share of local economic activity dependent on trade with the EU, making them more vulnerable to the negative economic consequences of this trade rupture. Also using EUREGIO data, Chen et al. (2018) estimate the different regional exposures to Brexit for UK and EU regions, observing important spatial heterogeneity. Another recent example of an external shock affecting regions in potentially different ways is the Covid-19 pandemic, whose impact was estimated to be higher in those regions specialized in accommodation and food services, such as island regions, as well as in regions where vehicle manufacturing accounts for an important share of their GDP (Prades and Tello-Casas, 2020). A similar analysis carried out by Ferraresi et al. (2024) for Italy finds that regions are affected differently by lockdown policies because of their heterogeneity in terms of consumption, investment or exports value chains.

Over the last decade, many factors have been identified that are related with the capacity of a place to adapt, resist and recover from economic downturns (see Martin and Sunley, 2014; and Kitsos, 2020), these ranging from the industrial structure of the local economies to institutional and geographical characteristics. Building on previous analyses of the relationship between local industrial structures and resilience, most studies have traditionally focused on sectoral composition, diversity and specialization patterns, as well as the relatedness and coherence of local industrial structures. Recently, however, attention has shifted towards the degree of embeddedness, understood as the share of intermediate economic activity taking place within the region. A region's degree of embeddedness, which can be captured by the inverse of an indicator of trade openness, might play a crucial role in understanding the uneven performance of regions and the spatial propagation of these external negative shocks. On the one hand, according to Kitsos et al. (2023), a high degree of embeddedness may generate positive externalities that assist a region facing a recession. These externalities correspond to the benefits accruing to firms from being close to their suppliers and purchasers and are manifested via formal and informal knowledge flows, innovation diffusion, and reduced transaction costs. On the other hand, excessive embeddedness can isolate regions from

technology diffusion channels, producing negative effects on business and harming regional development.

In the [Eaton and Kortum \(2002\)](#), [Caliendo and Parro \(2015\)](#) and [Caliendo et al. \(2018\)](#) theoretical trade models, the degree of embeddedness increases when: i) a region-sector experiences an increase in its fundamental productivity; ii) the fundamental productivity of this sector in other countries increases; and iii) the trade costs or the barriers to importing goods from other regions increase. The parameter moderating these effects can be interpreted as a trade elasticity. In these trade models, the trade elasticities explain how trade flows react to changes in geographical and economic trade barriers. As highlighted by [Simonovska and Waugh \(2014\)](#), this elasticity also helps measure trade frictions, predict trade responses to policy changes, and assess the economic gains or losses from trade, making it a crucial parameter in determining the degree of embeddedness, and thereby any changes in international trade.

In this paper we contribute to the literature on trade and regional economics by estimating trade elasticities at a subnational level. We estimate the sectoral trade elasticities among European regions using the production-based model recently introduced by [Carrascal-Incera and Orea \(2024\)](#). Following these authors, we use trade *and* production data to calculate the trade elasticities. Therefore, in contrast to previous empirical papers, we do not need data on bilateral trade flows in order to estimate our trade elasticities. The model is estimated using information from [Huang and Kouroumpis \(2023\)](#) for the period 2008-2018, which is the most recent trade flows database available for the European regions, this being combined with information from Eurostat and the BD.EURS database. As suggested by [Santamaria et al. \(2023\)](#), Europe and European regions prove particularly attractive for the study of regional trade flows due to several reasons. On the one hand, European regions exhibit a large degree of heterogeneity in terms of GDP per capita, growth patterns and population density. On the other, one of the EU's founding principles is to assure free trade among its members, eliminating some of the possible frictions to trade for all regions.

We also contribute to the literature on embeddedness by unravelling the potential dual role of a region's degree of embeddedness as a productivity driver or barrier. This objective is achieved by adapting the proxy-variable (PV) approach to macro-level data, in line with [Carrascal-Incera and Orea \(2024\)](#). These authors examine the consequences of embeddedness for the productivity performance of 42 major countries worldwide through two possible mechanisms: the so-called *efficiency effect*, whereby the fundamental productivity level of each region-sector increases due to the spatial proximity of interacting firms and sectors; and the *selection effect*, coined by [Caliendo et al. \(2018\)](#), whereby openness to trade facilitates access to cheaper intermediate inputs. The findings of [Carrascal-Incera and Orea \(2024\)](#) support the selection process introduced by [Caliendo et al. \(2018\)](#) but a heterogeneous efficiency effect across countries. We carry out a similar analysis using regional-level data from nine European countries.

Our final contribution has to do with the empirical literature on regional spillovers. This literature has generally produced mixed findings. For instance, [Tsiapa et al \(2025\)](#) find limited spatial spillovers attributable to productivity improvements in their application to regions in France, Germany, Italy and Spain. In contrast, [Liu and Cheng \(2021\)](#), [Han and Sickles \(2024\)](#) and [Liu and Sickles \(2024\)](#) highlight the importance of technological diffusion in driving productivity growth. They point out that the productivity growth occurring in supplier industries may bring know-how to downstream industries. Similarly, customer industries may stimulate learning and capability building in upstream industries. In this sense, investigating the extent of external spillovers through the global supply chain can therefore provide a more holistic understanding of the production environment in Europe and the implications for the technological diffusion of rules and regulations ([Liu et al. 2022](#)). As spillovers are expected in our application with macro-level data, we follow [Malikov and Zhao \(2023\)](#) and assume that

the (fundamental) productivity of a region-sector is governed by an endogenous Markov process that accommodates the cross-sectional dependence in region-specific productivity that said spillovers induce. In line with these authors, but using a parametric specification, our model permits the region-sector to improve its productivity by learning not only directly from its own productivity-modifying activities but also indirectly from the activities of other regions or sectors. However, whereas [Malikov and Zhao \(2023\)](#) provides a measure of the *immediate* indirect spillover effects of first-order neighbouring firms (production units) via the spatial weight matrix, our measure includes a *cascading* effect that arises from impacts on the production of higher-order (second-order, third-order and so on) neighbouring regions and upstream/downstream sectors via the input-output linkages across sectors and regions.

The rest of the paper unfolds as follows. [Section 2](#) introduces the theoretical background and econometric specification of our model. [Section 3](#) introduces the data sources, and the definition of the variables used to estimate both the trade elasticities. We present our empirical application in [Section 4](#) and conclude in [Section 5](#).

2. Theoretical background and econometric specification

2.1. Baseline specification

This subsection summarizes the main features of the production model introduced by [Carrascal-Incera and Orea \(2024\)](#) who bring attention to the fact that the Ricardian model of trade introduced by [Caliendo et al. \(2018\)](#) is closely connected to the estimation of trade elasticities. Both papers distinguish between two notions of productivity: fundamental productivity (F) and measured productivity (A). While *fundamental* productivity measures how much value added (V) can be produced with primary inputs (K and L),¹ *measured* productivity measures how much gross-output (Y) can be produced by combining not only primary inputs, but also material inputs (M) purchased from different regions.²

A major contribution of [Caliendo et al. \(2018\)](#) is to prove that measured productivity (A) can be expressed as a function of fundamental productivity (F) and the share of intermediate goods produced within the sector (Π). Based on their central equation, [Carrascal-Incera and Orea \(2024\)](#) proposed estimating the following production model:

$$\tilde{a}_{nt}^j = f_{nt}^j - \frac{1}{\theta_j} \tilde{\pi}_{nt}^j + \tau_{nt}^j \quad (1)$$

where subscript t stands for time, subscript n for region and superscript j for sector, θ is the elasticity of trade with respect to geographic barriers and other trade costs estimated for each sector, $(a_{nt}^j, f_{nt}^j, \pi_{nt}^j)$ are the logged values of $(A_{nt}^j, F_{nt}^j, \Pi_{nt}^j)$, and a tilde over a variable denotes that it is normalized by the value-added share in gross output (γ_{nt}^j). As logged fundamental productivity (f_{nt}^j) includes region-sector effects (see the next equation), τ_{nt}^j is a zero-mean

¹ [Carrascal-Incera and Orea \(2024\)](#) interpret F as a physical or non-pecuniary productivity concept because it has nothing to do with the cost of purchasing a particular intermediate good from one region or another. For instance, F captures a region-sector's state of technology, the existence of local economies of agglomeration and/or local knowledge spillovers, the abundance of natural resources, etc.

² Notice that, by rearranging the above two productivity notions, we can express the technology of each sector using a simple Cobb-Douglas production function as $Y = A[K^\beta L^{1-\beta}]^\gamma M^{1-\gamma}$, where γ is the share of value added in gross-output, β is the share of capital in value added, and M is a weighted average of material inputs which consist of goods from all sectors. [Carrascal-Incera and Orea \(2024, eq. 5\)](#) show that A depends on sector's fundamental productivity (down-weighted by the share of value-added on gross output) and on a complex term that captures the productivity effects associated with the benefits of international trade after a complicated arbitrage process where comparative advantage and trade costs have opposing effects on trade flows.

zero-mean noise term that captures both measurement errors in output and/or ex-post productivity shocks realized after period t decisions are made.³

The second term in equation (1) captures the productivity effects of an endogenous *selection* of firms if all regions move to a freer trade world. [Caliendo et al. \(2018\)](#) prove that the productivity impact of this selection process can be summarized entirely via the change in the region-sector's share of its own intermediate goods, which can be associated with a deterioration (recuperation) of the benefits of international trade. Later on, [Carrascal-Incera and Orea \(2024\)](#) takes advantage of the fact that this variable can be computed using the available output-input tables in order to propose a new method for computing trade elasticities based on the estimation of sectoral production functions where θ^j is calculated together with the technological parameters of equation (1).

In comparison with more traditional gravity models, the production function approach followed in this paper has the advantage of being theoretically grounded in a general equilibrium framework, where trade elasticities are estimated as part of a broader system of input substitution. In contrast, gravity models estimate trade elasticities by analysing how bilateral trade flows respond to changes in trade costs, typically in a partial equilibrium setting. This approach, however, is useful for providing a quick overview of the effect of trade policies on the volume of trade between two regions or countries. From an empirical perspective, our production model has the advantage of not requiring adjustments for zeros, as is often necessary in gravity models. Another advantage is that it allows for the measurement of the effect of embeddedness (or openness) on the economic performance of regions and countries. Our approach has two main disadvantages: (i) a poor representation of the region-sector production function may bias the estimation of trade elasticities; and (ii) it is more data demanding since it also requires collecting production data on region-sector's output and inputs.

2.2. More comprehensive specifications

We next build our empirical model based on [Carrascal-Incera and Orea \(2024\)](#)'s baseline specification. Our model extends equation (1) in three ways. First, as spillovers are expected in our application with macro-level data, we follow [Malikov and Zhao \(2023\)](#) and assume that a region-sector fundamental productivity is governed by a endogenous first-order Markov process with transition probabilities, represented by a function $h_t(\cdot)$, that can be expressed as follows:

$$f_{nt}^j = \alpha_n^j + h_t[f_{nt-1}^j, \pi_{n,t-1}^j, Wf_{nt-1}^j] + \xi_{nt}^j \quad (2)$$

where α_n^j is a region-sector effect,⁴ Wf_{nt-1}^j captures knowledge spillovers coming from neighbouring regions or sectors through supply relationships, ξ_{nt}^j is a transitory productivity shock that represents unpredictable uncertainty associated with productivity modifying activities, and the time subscript in h_t accommodates secular trends in productivity ([Doraszelski and Jaumandreu, 2013](#)).⁵ In line with [Carrascal-Incera and Orea \(2024\)](#), the function h_t in equation (2) includes productivity for the previous period (f_{nt-1}^j), which captures the persistence of the evolution process, and the previous period country's degree of embeddedness ($\pi_{n,t-1}^j$). The latter aims to capture local economies of agglomeration, local knowledge spillovers, and other synergies caused by spatial proximity of interacting firms and sectors. This allows us to account for (internal) *direct* learning taking place within the region-sector pair. Unlike [Carrascal-Incera and Orea \(2024\)](#), equation (2) enables the region-sector

³ [Carrascal-Incera and Orea \(2024\)](#) adopted later the PV approach to macro-level data and assumed that (logged) fundamental productivity follows an independent (over units) Markov process.

⁴ In their non-spatial Markov process, [Carrascal-Incera and Orea \(2024\)](#) assumed that $\alpha_n^j = \alpha^j + \alpha_n$.

⁵ We later use time trends to capture these productivity trends.

pair to influence the evolution of its productivity by interacting with other region-sector pairs as captured by $Wf_{nt-1}^j = \sum_{m \neq n}^N \sum_{k \neq j}^J w_{nm}^{jk} f_{mt-1}^k$. The weight terms w_{nm}^{jk} formalize the connectivity between the region-sector pair (n, j) and the region-sector pair (m, k) . We let the peer regions and sectors be identified based on their input-output linkages with region-sector pair (n, j) . We assume that for each region-sector pair (n, j) , the sum of spatial weight terms is equal to one. That is, we row-normalize all weights so that $\sum_{m \neq n}^N \sum_{k \neq j}^J w_{nm}^{jk} = 1$.⁶

Second, we use a specification of equation (1) where the elasticities of labour and capital are estimated, rather than computed, due to the lack of information on the shares of labour and capital.⁷ We only use the share of value added on gross output to control for the portion of region-sector's production function that depends on materials. Our empirical strategy thus resembles the two-step approach introduced by [Gandhi et al \(2020\)](#) to identify a firm's production function and productivity, but we do not first estimate a materials share equation because this would require assuming that all sectors and regions maximize short-run profits, likely a strong assumption in a macro-level setting. If we plug (2) into (1), assuming a linear Markov fundamental productivity process as in [Carrascal-Incera and Orea \(2024\)](#), and taking into account that we are forced to estimate the portion of the production function that depends on capital and labour, we can then express the technology of each region-sector pair (n, j) using a simple Cobb-Douglas production function as follows:⁸

$$\tilde{y}_{nt}^j = \alpha_n^j + \alpha_t t + \alpha_{tt} \frac{1}{2} t^2 + \beta k l_{nt}^j + \rho_F f_{nt-1}^j + \rho_W W f_{nt-1}^j + \rho_\pi \pi_{n,t-1}^j - \frac{1}{\theta^j} \tilde{\pi}_{nt}^j + \tau_{nt}^j + \xi_{nt}^j \quad (3)$$

where $\tilde{y}_{nt}^j = \tilde{y}_{nt}^j - (1 - \gamma_{nt}^j) \tilde{m}_{nt}^j - l_{nt}^j$, and $kl_{nt}^j = k_{nt}^j - l_{nt}^j = \ln(K_{nt}^j/L_{nt}^j)$. Three comments are in order regarding equations (3). First, in line with [Carrascal-Incera and Orea \(2024\)](#), we take advantage of the fact that we observe the shares of value added in gross output (γ_{nt}^j) as working with a parsimonious specification of our production model. More concretely, equation (3) does not require estimating the elasticity of gross output with respect to the amount for material inputs as it is assumed to be equal to $1 - \gamma_{nt}^j$. Second, we have obtained our dependent variable (\tilde{y}_{nt}^j) after carrying out several adjustments in gross output. We first subtract the contribution of material inputs to gross output. We then normalize the whole equation (including the attenuated output) using the shares of value added in gross output (γ_{nt}^j), as per [Carrascal-Incera and Orea \(2024\)](#). Finally, as the contribution of capital and labour to value added sum to unity, we subtract the amount of labour and leave capital deepening as the unique production factor. Third, note that ρ_F in equation (3) measures the degree of persistence of the evolution process, ρ_π measures the importance of the local synergies caused by the spatial proximity of interacting firms and sectors, and ρ_W measures the spatial effects from neighbouring regions.

[Malikov and Zhao \(2023\)](#) illustrates this feature of our spatiotemporal autoregressive model as follows. By letting f_{nt}^j depend on the region-sector pair (n, j) 's own productivity modifier $\pi_{n,t-1}^j$, we are able to account for (internal) direct learning taking place within the

⁶ As is customary in the PV approach, we assume in equation (2) that the improvements in a region-sector pair's fundamental productivity, either through internal learning or from peers, take a period to materialize.

⁷ [Liu and Cheng \(2021\)](#) and [Liu and Sickles \(2024\)](#) also estimate a production function where the elasticities of the production factors are estimated, rather than computed.

⁸ In keeping with most of the earlier literature, both value-added and gross production are at constant returns to scale (CRS). On the one hand, [Caliendo et al. \(2018\)](#) used the CRS assumption to model value added to comply with the identity between value added and the income from labour and capital. On the other hand, [Zelenyuk \(2024\)](#) has recently provided a solid theoretical justification for the use of a CRS technology at a macro-level or industry-level. This justifies using the CRS assumption to model gross output as well.

region-sector pair (n, j) . The *direct* marginal effect can be computed as $\partial h_t / \partial \pi_{n,t-1}^j$. Note that, in our application, this derivative is equal to $\hat{\rho}_\pi$. [Malikov and Zhao \(2023\)](#) measures the region-sector pair (n, j) 's *indirect* learning from region-sector pair (m, k) 's productivity-modifying activities as $\partial h_t / \partial \pi_{m,t-2}^k$. As this indirect effect is defined for a pair of region-sector pairs, [Malikov and Zhao \(2023\)](#) aggregates all the individual *indirect* marginal effects to obtain the total indirect spillover effect from all of the region-sector pair (n, j) 's peers as $\sum_{m \neq n}^N \sum_{k \neq j}^J \partial h_t / \partial \pi_{m,t-2}^k$. The *total* marginal effect of a unit change in *all* region-sectors' degrees of embeddedness can be simply computed as $\partial h_t / \partial \pi_{n,t-1}^j + \sum_{m \neq n}^N \sum_{k \neq j}^J \partial h_t / \partial \pi_{m,t-2}^k$. Note that, in our application, the individual indirect effect is equal to $\hat{\rho}_W w_{nm}^{jk} \hat{\rho}_\pi$ and therefore the total effect collapses to $\hat{\rho}_\pi + \hat{\rho}_W \hat{\rho}_\pi \sum_{m \neq n}^N \sum_{k \neq j}^J w_{nm}^{jk}$. Finally, as we row-normalize all weights so that $\sum_{m \neq n}^N \sum_{k \neq j}^J w_{nm}^{jk} = 1$, the total indirect spillover effect in [Malikov and Zhao \(2023\)](#) is equal to $\hat{\rho}_\pi + \hat{\rho}_W \hat{\rho}_\pi$.

[Malikov and Zhao \(2023\)](#) point out that their total indirect spillover effect is “short run” as they recognize that their measure ignores cumulative feedback effects across both regions and sectors, as well as ignoring these effects over time owing to the persistent nature of the region-sector pair's productivity evolution. To achieve long run effects of embeddedness on region-sector pairs' fundamental productivity, we proceed as follows. We first adjust the estimated short-run effect of embeddedness on region-sector pairs' fundamental productivity ($\hat{\rho}_\pi$) using the estimated temporal autoregressive coefficient ($\hat{\rho}_F$) to take into account the degree of persistence of the evolution process. The long-run (but still non-spatial) effect is therefore $\hat{\hat{\rho}}_\pi = \hat{\rho}_\pi / (1 - \hat{\rho}_F)$. We next adjust the estimated short-run effect of embeddedness to reflect the degree of cross-sectional correlation between region-sectors' fundamental productivities.

In a typical spatial autoregressive model where $f_t = (f_{1t}, \dots, f_{Nt})$ is modelled as a function of a *contemporaneous* spatial lag component (Wf_t), the marginal effect of an explanatory variable contained in $x_t = (x_{1t}, \dots, x_{Nt})$ is obtained once the model is specified using a matrix notation: the *contemporaneous* spatial lag is moved to the left-hand side of the model and the following matrix of derivatives is computed: $\partial y_t / \partial x_t = (\partial y_{1t} / \partial x_t, \dots, \partial y_{Nt} / \partial x_t) = (I - \rho W)^{-1} \beta$, where ρ is a spatial autoregressive parameter and β is the coefficient of the explanatory variable contained in x_t . Our spatiotemporal autoregressive Markov process in equation (3) does not allow us to follow the same procedure for obtaining global spatial spillovers because it is not possible to take a common factor for the dependent variable when the *lagged* spatial lag component is moved to the left-hand side of equation (3) since $f_t \neq f_{t-1}$. Nevertheless, [Skevas \(2020\)](#) points out in a similar spatiotemporal autoregressive setting that given the modelling approach presented in equation (3), the typical matrix of derivatives can still be used in our spatiotemporal autoregressive setting, although it now refers to long-run fundamental productivity.⁹

Inspired by [Skevas \(2020\)](#), we propose measuring the spatial long-run effects of embeddedness on region-sector pairs' fundamental productivity as $(I - \hat{\rho}_W W)^{-1} \hat{\beta}$, where $\hat{\beta} = \hat{\rho}_\pi$ if we do not take into account the autoregressive persistence in productivity, and $\hat{\beta} = \hat{\hat{\rho}}_\pi$ if we do. The diagonal and off-diagonal elements of $(I - \hat{\rho}_W W)^{-1} \hat{\beta}$ represent *direct* and *indirect* marginal effects respectively. Both effects include a feedback effect, which passes through other units via the spatial multiplier matrix and back to the unit which initiated the change. [LeSage and Pace \(2009\)](#) suggest reporting a *scalar* summary measure - concretely, the *mean*

⁹ [Skevas \(2020\)](#) states that this conclusion can be reached if one applies recursive substitution for past values of f over t periods in equation (3) and stationarity is assumed. This is because stationarity allows one to define a distribution for the first period, which is needed to initiate the autoregressive process of a latent variable such as f .

values - of both the direct and indirect effects. While the mean *direct* marginal effect is computed as a simple arithmetic average of the diagonal elements of $(I - \hat{\rho}_W W)^{-1} \hat{\beta}$, the mean *indirect* marginal effect is computed as the average of the row or the column sums of the off-diagonal elements of that matrix. Note finally that in this sense, as pointed out by [LeSage and Pace \(2014, p. 6\)](#), the global multiplier $(I - \hat{\rho}_W W)^{-1}$ can be expressed as $I + \hat{\rho}_W W + (\hat{\rho}_W^2 W^2 + \hat{\rho}_W^3 W^3 + \dots)$. This implies that $(I - \hat{\rho}_W W)^{-1} \hat{\beta}$ can be decomposed into a non-spatial effect ($\hat{\beta}$) via the identity matrix ($\hat{\beta}$), plus an immediate (local) effect that produces impacts on the production of first-order neighbouring units via the spatial weight matrix ($\hat{\rho}_W W \hat{\beta}$) as in [Malikov and Zhao \(2023\)](#), together with a cascading (global) effect that arises from impacts on the production of second-order neighbouring region-sector pairs via $\hat{\rho}_W^2 W^2$ and so on.

Finally, a third distinction with respect to [Carrascal-Incera and Orea \(2024\)](#) is that f_{nt-1}^j is not observed in our more granular geographical application. In order to address the latency of region-sector fundamental productivity in order to estimate (3), we approximate f_{nt-1}^j as a residual, i.e., the part of the value added not explained by the performance of labour or capital. If the value-added production function is again Cobb-Douglas, we can express f_{nt-1}^j as:

$$f_{nt-1}^j = v l_{nt-1}^j - \beta k l_{nt-1}^j + z_{nt-1}^j \quad (4)$$

where $v l_{nt-1}^j = v_{nt-1}^j - l_{nt-1}^j = \ln(V_{nt-1}^j / L_{nt-1}^j)$, V_{nt-1}^j is region-sector pair (n, j) 's value added in period $t - 1$, and z_{nt-1}^j can be interpreted as a measurement error.¹⁰ If we approximate $W f_{nt-1}^j$ in a similar fashion, we obtain the final specification of our empirical model:

$$\begin{aligned} \tilde{y}_{nt}^j = & \alpha_n^j + \alpha_t t + \alpha_{tt} \frac{1}{2} t^2 + \beta k l_{nt}^j + \rho_F v l_{nt-1}^j - \rho_F \beta k l_{nt-1}^j + \rho_W W v l_{nt-1}^j - \\ & \rho_W \beta W k l_{nt-1}^j + \rho_\pi \pi_{n,t-1}^j - \frac{1}{\theta^j} \tilde{\pi}_{nt}^j + \varepsilon_{nt}^j \end{aligned} \quad (5)$$

where $\varepsilon_{nt}^j = \tau_{nt}^j + \xi_{nt}^j + \rho_F z_{nt-1}^j + \rho_W W z_{nt-1}^j$. It is worth highlighting at this point that the parameter β is not an elasticity. This parameter simply separates the elasticity of gross output with respect to value-added (γ_{nt}^j) into two elasticities, i.e., the elasticities with respect to labour ($\beta_{L,nt}^j = (1 - \beta) \gamma_{nt}^j$) and capital ($\beta_{K,nt}^j = \beta \gamma_{nt}^j$). Note that, despite $\beta_{L,nt}^j$ and $\beta_{K,nt}^j$ varying across sectors and regions (and over time), the ratio $\beta_{L,nt}^j / \beta_{K,nt}^j = (1 - \beta) / \beta$ is common to all regions and sectors. As this is likely to be a strong assumption, in our application we estimate both Cobb-Douglas and Translog specifications for the value-added production function. In our Translog model, we also allow for biased technical change.

Therefore, in our more comprehensive specification, we include squared terms and interactions with the time trend in both equations (4) and (5). More concretely, the Translog specification of equations (4) and (5) can be expressed respectively as:

$$f_{nt-1}^j = v l_{nt-1}^j - \beta k l_{nt-1}^j - \delta_{\frac{1}{2}} (k l_{nt-1}^j)^2 - \eta k l_{nt-1}^j \cdot (t - 1) + z_{nt-1}^j \quad (6)$$

$$\begin{aligned} \tilde{y}_{nt}^j = & \alpha_n^j + \alpha_t t + \alpha_{tt} \frac{1}{2} t^2 + \beta k l_{nt}^j + \delta_{\frac{1}{2}} (k l_{nt}^j)^2 + \eta k l_{nt}^j \cdot t + \rho_F v l_{nt-1}^j - \rho_F \beta k l_{nt-1}^j - \\ & \rho_F \delta_{\frac{1}{2}} (k l_{nt-1}^j)^2 - \rho_F \eta k l_{nt-1}^j \cdot (t - 1) + \rho_W W v l_{nt-1}^j - \rho_W \beta W k l_{nt-1}^j - \rho_W \delta_{\frac{1}{2}} (W k l_{nt-1}^j)^2 - \\ & \rho_W \eta W k l_{nt-1}^j \cdot (t - 1) + \rho_\pi \pi_{n,t-1}^j - \frac{1}{\theta^j} \tilde{\pi}_{nt}^j + \varepsilon_{nt}^j \end{aligned} \quad (7)$$

To conclude this subsection, recall that [Carrascal-Incera and Orea \(2024\)](#) takes advantage of the fact that $\tilde{\pi}_{nt}^j$ can be computed using the available output-input tables to estimate the trade elasticities captured by θ^j in equations (5) and (7). As such, these equations treat the coefficient of the normalized region-sector's share of its own intermediate goods as

¹⁰ We thank Referee #1 for bringing to our attention that our residual measure must contain a measurement error.

an additional parameter of the model, in line with [Caliendo and Parro \(2015\)](#) and previous papers. Inspired by these authors, in our application we use a set of sector and country-specific parameters (effects) to obtain the point estimates of trade elasticities. A second empirical strategy for computing trade elasticities involves the parameterization of the trade elasticities as a *function* of a set of covariates. In our application, we include both sector and country-specific parameters, a time trend, and a set of regional and sectoral covariates.¹¹

2.3. Final remarks on our identification strategy

In this subsection we explain better our identification strategy and compare it with the typical sequential estimation procedure used in the proxy-variable approach. Since [Gandhi et al \(2020\)](#), a firm’s production function is typically estimated using a two-step procedure. The main advantage of their two-step procedure is that no instruments are needed for the freely-varying input, which is the materials input (M) in both our application and in many firm-level data applications. They first suggest estimating a materials share equation that is obtained after exploiting the firm’s (static) first-order condition of profit maximization with respect to M under risk neutrality and perfectly competitive markets. The first step allows estimating the part of the production function that is related to the endogenous variable input M . The remaining part of the production function can be estimated in a second step without the endogeneity problem once the lagged firm’s persistent productivity is replaced with a proxy.

In our setting, this requires assuming that all sectors and regions maximize their short-run profits when choosing the optimal freely varying inputs. Notice that this is likely a strong assumption in a macro-level setting given the extensive empirical literature on misallocation - pioneered by [Restuccia and Rogerson \(2008\)](#) and [Hsieh and Klenow \(2009\)](#). Moreover, [Jones \(2011\)](#) has postulated that ignoring inter-sectoral linkages in production may result in an underestimation of economic losses due to misallocation. More recently, while [Hang et al. \(2020\)](#) find empirical evidence of non-negligible intermediate input distortions, [Gong and Sickles \(2024\)](#) find that the estimated productivity loss attributable to financial frictions during the Great Recession, was substantial. For this reason, in our application to European regions and sectors, we follow the growth accounting literature and replace the output elasticity of materials (ε_M) with the observed share of materials in gross output ($S_M = 1 - \gamma$). Note that, by doing so, we do not circumvent the need to assume profit maximization at both sectoral and regional level since this is often a requirement for such a replacement. Our approach, however, is more conservative as it does not rely explicitly on estimating a first-order condition of profit maximization that is suitable for firms but not for sectors and regions due to the aforementioned misallocation issue amongst others. For instance, the conventional materials share equation ignores the fact that producers purchase intermediate goods from different regions and that the presence of intermediate input distortions (such as taxes/subsidies that are not directly recorded as costs of intermediate inputs) does matter in terms of the firm’s profit maximization problem (see, e.g., [Hang et al. 2020](#)). Note, however, that the remaining unknown parameters of our model (including capital and labour elasticities) are estimated once we remove the production attributable to the use of materials from total gross output in line with [Gandhi et al \(2020\)](#). In this sense, our first-step equations (5) and (7) can be viewed as a version of their second-step production equation that, in a macro-level setting, also includes trade related productivity terms.

¹¹ This specification uses the following function for the trade elasticities:

$$\theta_{nt}^j = \frac{-1}{\tau_c + \tau_j + \tau_t t + \tau_x x_{nt}^j}$$

where subscript c stands for country, τ_c and τ_j are respectively country and sector-specific effects, x_{nt}^j is a vector of trade elasticity covariates, and τ_x is a vector of parameters to be estimated.

Moreover, it is worth highlighting that, according to the conventional structural assumptions in the PV approach, there are no endogenous independent variables in equations (5) and (7), and hence these can be estimated using the Least Squares (LS) method.¹² For instance, in line with e.g., [Malikov and Zhao \(2023\)](#) and [Hou et al. \(2024\)](#), we assume that both actual capital (k_{nt}^j) and labour (l_{nt}^j) are quasi-fixed inputs and determined in period $t - 1$, and thus can be treated as exogenous regressors. Note also that the Markov process in (2) assumes that the productivity innovation ξ_{nt}^j is realized after $\pi_{n,t-1}^j$ and Wf_{nt-1}^j are fully determined. This implies that the productivity shocks in period t cannot be anticipated in period $t - 1$, and hence that our variables determined/observed in period $t - 1$ are exogenous. Nevertheless, a possible objection to using LS is that our empirical model might be underspecified due to the (normalized) own trade share variable being an endogenous variable. [Carrascal-Incera and Orea \(2024\)](#) point out that this problem vanishes if we also assume that changes in a region-sector's degree of embeddedness are costly and thereby subject to delay. This implies that the actual degree of embeddedness ($\tilde{\pi}_{nt}^j$) is a state variable that can be treated as well as predetermined and as such, should not be instrumented.

Finally, note that our approach is fully parametric, in contrast to [Gandhi et al.'s \(2020\)](#) nonparametric approach. This allows us to estimate our model by using a linear FE estimator. Otherwise, identification of our production model in equations (5) and (7) would likely prove very complicated due to the presence of (nested) nonparametric functions requiring evaluation at multiple data points (see [Malikov and Zhao, 2023, p. 1214](#)).

3. Data

The regional macroeconomic data used in this study have been obtained from different sources, but primarily from the recently released Multi-Regional Input-Output (MRIO) database developed by [Huang and Kouroumpis \(2023a\)](#), hereafter referred to as the HK database. This database, which was published in *Nature (Scientific Data)*¹³, contains the information on Gross Output (Y), Value-Added (V) and Intermediate Inputs or Materials (M) needed to perform the analysis and calibration of the model described in the previous section. Additionally, the HK database includes detailed region-sector trade flow data required to compute the W matrix¹⁴ and to calculate the share of intermediate goods produced within each region (denoted as π). The HK database covers the period 2008-2018 for 272 NUTS-2 European Regions and 10 different sectors. To the best of our knowledge, it is the most detailed and up-to-date dataset available about the economic and trade structure of the EU regions.

This estimation of regional trade data by [Huang and Kouroumpis \(2023a\)](#) combines survey and non-survey methods, using information from the OECD, Eurostat, road freight flows linked to the 2013 trade data from the ETISPlus database ([Speth et al. 2022](#)), and the EUREGIO database ([Thissen et al. 2018](#)). The authors validated the HK database by comparing its results with those from the EUREGIO database for the overlapping period (2008 to 2010). They observed relatively small differences or errors between the two databases, with a linear correlation of 0.8, thereby indicating the robustness of the HK database.

¹² In our application, we use a Fixed-Effect (FE) estimator due to both equations include region-sector effects (α_n^j).

¹³ We specifically use the dataset from [Huang and Kouroumpis \(2023b\)](#), publicly available at <https://zenodo.org/records/7765776> in its version v11, released on May 7, 2024.

¹⁴ We use a symmetric W matrix for the year 2008 that aggregates both downstream and upstream flows of intermediate goods. This matrix is row-normalized with the row-sum of intermediates.

For our production-based model, we require additional variables that are not included in the HK database, specifically the primary inputs: Employment (L)¹⁵ and Capital Stock (K). Employment data are obtained from the Eurostat Labour Force Survey, using the same sectoral disaggregation and time coverage as the HK database. In contrast, there is a lack of Capital Stock data at the regional (subnational) level for Europe, making it the limiting factor in our analysis. To address this, we employ a simple estimation combining data from two complementary databases: the EUKLEMS & INTANProd (Bontadini et al. 2023) and the BD.EURS (Escribá and Murgui, 2014a; 2014b; Escribá et al. 2019).

Capital Stock at the national level is obtained from the latest release of the EUKLEMS database, which we use as the reference value. The EUKLEMS database provides information on net Capital Stock for all assets across European countries, for the period spanning from 1995 to 2020 and accounts for a total of 42 different industries. In a later step, using information from the BD.EURS database, we allocate the national Capital Stock among the different regions within each country. The BD.EURS database contains information on Gross Value Added (V) at both current and constant prices, Employment (L), and Capital stock (K). The key contribution of this database lies in the estimation of Capital Stock at the regional level. However, the BD.EURS database is limited to nine countries (Belgium, Germany, France, Italy, The Netherlands, Austria, Portugal, Sweden and Spain) over the period 1995-2014 and includes data for six aggregated 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).

Due to the limitations of the BD.EURS database as the only source of Capital Stock at the regional level, and after checking the correspondences with the HK database, we end up with data for nine countries and 120 regions. It should be noted that German regions are represented at NUTS 1 level rather than NUTS 2, in line with the spatial disaggregation in BD.EURS. We keep the 2008-2018 period and the 10-industry disaggregation, following the time and sectoral dimensions of the HK database. To distribute the total national Capital Stock by industries from 2008 to 2014, we apply the regional shares from BD.EURS. For the subsequent years (2015–2018), we extend the 2014 subnational shares, based on the observed high stability of regional Capital Stock shares during the 2008–2014 period. For industry disaggregation, the regional shares of the aggregated sectors from BD.EURS are used to distribute Capital Stock across the disaggregated sectors in our database. The national totals of each sector and its evolution over time is known from EUKLEMS. As an example, the regional shares for Sector OU in BD.EURS are used to distribute Capital Stock for Sectors O-Q and R-U in our dataset. This approach allows us to preserve regional heterogeneity across sectors for the remaining variables, avoiding the need to aggregate everything into six broad sectors.

Finally, it is worth mentioning that, in this paper, instead of using *physical* distance to create the spatial W matrix, we use the sectoral input and output flows based on the EU Input-Output tables to measure *economic* distance between industries within/across the NUTS2 economies considered. Liu and Sickles (2024) suggest that intermediate flows can better represent the channels for knowledge diffusion, communication and cooperation in production among industries. The descriptive statistics for the data used in our model, including the additional variables and parameters (such as the value added to gross output ratio and

¹⁵ While growth models often include variables such as human capital (sometimes distinguishing between skill categories) and public investment (Álvarez and Barbero, 2016), the lack of disaggregated data at the regional-sectoral level across Europe prevents us from incorporating them into our current analysis. To try to account for this limitation, our specification includes region-sector specific fixed effects, which help capture some of the unobserved heterogeneity associated with differences in skill composition across sectors, among other possible issues. Additionally, since the shares of high and low skill labour evolve similarly by regions and sectors, the effect of these labour trends is captured by the time trend variables.

population density for NUTS2 regions), are reported in [Table 1](#). To convert figures from current to constant values, we use the GDP deflators obtained from the Eurostat and European Central Bank calculations. The 120 regions and 10 sectors included in our analysis are detailed in [Table A1](#) and [Table A2](#) in Appendix A.

[Insert Table 1 here]

4. Results

We split this section into three subsections. In the first one, we focus our analysis on the Markov process of region and sectorial fundamental productivity and discuss the existence of spatial spillover effects through the global supply chain. In the next subsection we present the parameter estimates of several models with heterogeneous trade elasticities. The last subsection is devoted to examining the overall productivity effect attributable to the degree of embeddedness.

4.1. Models with a homogeneous trade elasticity.

Several models are estimated in this subsection using both Cobb-Douglas and Translog specifications for the value-added production function. In all of them, we restrict the trade elasticity to be common to all sectors and regions. This strong restriction is relaxed in the second subsection. All production functions include individual effects as well as time trends (the set of time dummies yield qualitatively similar results). While the time trends are used as a placeholder to summarize common shocks, the region-sector specific effects included in all estimated specifications aim to capture the production differences attributable to relevant but unmodelled 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. The CRS assumption allows using a very parsimonious production function with a unique production factor (i.e., capital deepening) to represent region-sector technology.

The parameter estimates of four production models with homogeneous trade elasticities are shown in [Table 2](#). Most of our parameter estimates have the expected sign and our results are sound despite the fact that we later find evidence of heterogeneity in the trade elasticities. Model 1 uses a Cobb-Douglas production function with a Hicks-neutral technological progress. The coefficient of capital deepening is 0.855 and statistically different from zero and unity. That is, while the elasticity of gross output with respect to capital is 85.5% of the total elasticity attributable to value added, the elasticity of labour only represents the 14.5% of the elasticity of value added. Therefore, unlike many previous studies using cross-country data, we find that the regional and sectorial elasticity of labour is much smaller than the elasticity of capital. Models 2, 3 and 4 use a Translog specification for the production function that includes the square of capital deepening. In addition, Models 3 and 4 interact capital deepening with the time trend to allow for non-neutral technical change. Note that the second-order coefficient is significant for all the Translog specifications, indicating that the elasticity of capital is not common to all region-sector pairs. The positive value found for this coefficient suggests that the elasticity of capital is larger in regions/sectors with a greater capital deepening. The coefficients of the time trend t are significant and negative in all specifications, indicating that the economic environment has worsened over time, reducing regions' productivity. The non-neutral specification used in Models 3 and 4 allows us to qualify this result even further. The negative coefficient found for the interaction of capital deepening with the time trend suggests that, on average, the regions and sectors with larger capital-labour ratios have suffered more from the economic environment deterioration.

[Insert Table 2 here]

We next focus our analysis on the Markov process of fundamental productivity. Model 1 simply uses a linear specification that only includes the lagged values of a region-sector's degree of embeddedness, the temporally lagged values of a region-sector's value added per worker and capital per worker and the spatially lagged values of these two production-type

variables. If the value-added production function is extended with square and interaction terms, the Markov process should be extended accordingly. For this reason, the Markov process of Models 2, 3 and 4 also includes temporally and spatially lagged values of regions and sectors' value added and capital per worker. Recall that the coefficient of lagged value added per worker is nothing more than the coefficient of lagged fundamental productivity (ρ_F) in equation (8). This coefficient measures the degree of persistence of the evolution process. This coefficient is positive and close to 0.5 in all specifications of our model, indicating a significant but moderate degree of persistence in a region-sector's fundamental productivity.¹⁶ As expected, the coefficients of the production factors (e.g., lagged capital per worker) included in the Markov process do have the opposite (negative) sign to the production function and tend to be smaller in absolute terms.

Regarding the spatially lagged variables included in the Markov process, it is worth mentioning that many of the so-called *SLX variables* in Table 2 are statistically significant. Recall that the coefficient of the spatially lagged value of value added per worker coincides with the spatial autoregressive parameter (ρ_W) that measures the degree of cross-sectional correlation between region-sectors' fundamental productivities. We find that this coefficient is positive and statistically significant for all the specifications. Therefore, the productivity level of neighbouring regions or sectors positively affects a region-sector's productivity through input-output linkages, in accordance with other studies using regional data. The estimated coefficient of lagged fundamental productivity (ρ_F) is close to 0.5 for all the specifications, whereby an increase of region's own fundamental productivity by 10 percentage points boosts its productivity the following year by 5%. As expected, the effect of an increase in the fundamental productivity of a neighbouring region or sector is smaller in magnitude. The estimated spatial autoregressive coefficient is close to 0.31, so that a 10 percentage point increase in a neighbouring region or sector boosts a region's fundamental productivity by only 3.1%.

The estimated Markov process also allows us to examine the first channel through which the degree of embeddedness (openness) might promote a region-sector pair's productivity, i.e., the so-called efficiency effect. The target coefficient for examining this is the coefficient of lagged degree of embeddedness. Interestingly, the four models shown in Table 2 do not support the existence of either positive or negative local externalities, as the coefficient of this variable proves to be insignificant. In the next subsection we will examine whether this result is robust to modelling issues.

Finally, we turn our attention to the coefficients that allow us to compute *trade elasticities*. The coefficient of the (normalized) region-sector's share of its own intermediate goods is negative and statistically significant.¹⁷ This provides empirical evidence supporting the so-called *selection process* introduced by Caliendo et al, (2018) to justify the propagation of local productivity shocks across sectors and countries. The trade elasticity is simply the negative of the inverse value of the estimated coefficient of normalized region-sector's share of its own intermediate goods. The small values shown for these coefficients in Table 2 yield trade elasticities that are not only far from the values for trade elasticities found on average in the literature (see, e.g., Carrascal-Incera and Orea, 2024, Figure 5), but also from those found in the next subsection using specifications that do not impose a common trade elasticity for all regions and sectors. Thus the estimated trade elasticities are biased upwards because of this issue.

4.2. Models with heterogeneous trade elasticities.

¹⁶ In our previous paper using country-level data we found a higher degree of persistence as it proved to be close to 0.96, a somewhat expected result.

¹⁷ Model 4 allows the common trade elasticity to vary over time, but this more flexible specification yields qualitatively similar results to the estimated coefficient of the time trend which is roughly equal to zero.

While in the previous subsection we focused our discussion on the specification of a region-sector's fundamental productivity assuming a common trade elasticity, in this subsection we estimate sector-specific trade elasticities. [Table 3](#) shows the parameter estimates of four models with heterogeneous trade elasticities. All of them are extensions of the most comprehensive but homogeneous-coefficient model (Model 4) shown in [Table 2](#). As in Model 4, our trade elasticity function in [Table 3](#) always depends on the time trend. Model A in [Table 3](#) replaces the single coefficient of the normalized region-sector's own trade share of Model 4 with a set of sector-specific coefficients. Model B extends the previous one by adding a set of country-specific coefficients for the normalized region-sector's own trade share. These two models allow estimating sector and country-specific trade elasticities. A common feature of these two models is that they treat the trade elasticities as parameters, where these vary over time because we allow the trade elasticities to depend on the time trend. The next two models interact the region-sector's own trade share with a set of covariates. In line with [Carrascal-Incera and Orea \(2024\)](#), Models C and D parameterize the trade elasticity using a parametric function of the within-country standard deviations of both the share of value added in gross output (SD_V^j) and the own trade shares of intermediates (SD_π^j). Note that the two standard deviations vary across countries and sectors, but not across regions. Model D also includes population density to measure the effect of regions' urbanization on trade elasticities, thereby allowing for regional heterogeneity in estimated trade elasticities. Finally, it should be kept in mind that all heterogeneous-coefficient models include sector and country-specific effects in their trade elasticity function.¹⁸ Therefore, Models C and D combine the two empirical approaches proposed in Section 3 to obtain point estimates of trade elasticities.

[Insert Table 3 here]

Our previous findings stay the same once we allow for heterogeneous trade elasticities: there are larger elasticities of capital in regions and sectors with a larger capital/labour ratio; fundamental productivity exhibits a significant but moderate degree of persistence over time; and productivity spillovers are positive and significant. Note, however, that the coefficient of the lagged degree of embeddedness is now positive and statistically significant. Therefore, in line with the findings of [Carrascal-Incera and Orea \(2024\)](#) using country-level data and with the previous literature summarized by [Kitsos et al. \(2023\)](#), our models with heterogeneous trade elasticities provide empirical evidence supporting the existence of positive agglomeration and proximity externalities during the period considered.

Several comments are in order regarding the parameter estimates that will be used later to compute trade elasticities. First, we always reject the null hypothesis of a common sectorial trade elasticity using LR tests. These tests thus support the existence of heterogeneous trade elasticities among our set of European regions. Second, in line with [Carrascal-Incera and Orea \(2024\)](#), there is weak evidence indicating that the trade elasticities change over time during the global financial crisis.¹⁹ Third, we find a positive and statistically significant coefficient for the within-country standard deviation of the share of value added in gross output. In contrast, we do not find a significant coefficient for the within-country standard deviation of the own trade shares of intermediates. This coefficient proved to be statistically significant in [Carrascal-Incera and Orea \(2024\)](#) but using between-country standard deviations of the own trade shares of intermediates. Fourth, the coefficient for population density is positive and statistically significant, indicating that the most-populated regions tend to have larger trade elasticities. Finally, most of the sector and country-specific effects that interact with the normalized region-sector's share of its own intermediate goods (not shown) are negative and statistically significant, as predicted by [Caliendo et al. \(2018\)](#)'s theoretical trade model. The findings in

¹⁸ The regional and sectoral-specific effects are not reported in [Table 3](#) for space limitations.

¹⁹ [Fontagné et al \(2022\)](#) also find that their trade elasticities are basically sticky over time (i.e., almost time-invariant).

Carrascal-Incera and Orea (2024) support the selection process introduced by Caliendo et al. (2018). We do the same but, in this case, using regional-level data from nine European countries. In the Caliendo et al. (2018) framework, the selection effect always has a positive effect on a region and sector's measured productivity. This also occurs in our empirical application because we find negative coefficients for the (normalized) own trade share variable in equation (14). Considering that this measure of embeddedness can be also understood as the inverse of a relative openness indicator, we find that measured TFP is positively associated with openness via cheaper intermediate goods.

Our application shows that the novel approach proposed by Carrascal-Incera and Orea (2024) for estimating trade elasticities based on a production model again can provide sound trade elasticities. Appendix B includes two tables with the estimated trade elasticities of each sector and country, and Figure 1 depicts the sectoral and national trade elasticities that have been computed using our more comprehensive specifications (Model D). As the trade elasticity is nothing other than the inverse value of the estimated coefficient of normalized region-sector's share of its own intermediate goods, extremely large or small trade elasticities are obtained when the estimated coefficient is close to zero. To reduce the influence of abnormal trade elasticities, we present the median values of the trade elasticities of each group.²⁰

As we can see in Figure 1, the median trade elasticities have the correct sign, and the magnitude of the estimates varies considerably across sectors. That is, in line with the papers that have estimated trade elasticities at a sectorial/product level, our findings support the existence of heterogeneous trade elasticities across different sectors. As expected, the sectoral trade elasticities for the non-tradable sectors (construction and services) are much smaller than the ones for the tradable sectors (industry and agriculture). However, it is worth highlighting that the estimated trade elasticities for construction and services are far from zero. Therefore, in general they cannot be considered as *fully* non-tradable sectors as has often occurred in previous studies. Our findings suggest a range for the trade elasticity of 14.03 to 20.04 for the tradable sectors and a range for the trade elasticity of 2.33 to 8.27 for the non-tradable sectors. Our application to the European regions provides slightly larger trade elasticities than those found in Carrascal-Incera and Orea (2024) using country-level data. Because the inverse of this elasticity linearly controls changes in real income necessary to compensate a representative consumer for going to autarky in the Ricardian trade model firstly introduced by Eaton and Kortum (2002), our estimates reduce the measured welfare gains from trade relative to our previous findings.

We now turn to the geographical heterogeneity of the estimated trade elasticities. In international economics and macroeconomics, this is a fundamental parameter for the evaluation of welfare gains from trade, as well as for understanding the consequences of trade policies and the international transmission of macroeconomic shocks. However, as pointed out by Fontagné et al (2022), despite the great importance of this parameter for scholars, practitioners and policy makers, there is a lack of complete and reliable estimates of product-specific trade elasticities in the previous literature. Figure 1 also depicts the country median trade elasticities that have been computed using Model D. Except for France, we obtain positive trade elasticities for all countries.²¹ Note that France is not depicted in Figure 1 for presentation purposes.²² The largest trade elasticities are found in Portugal, the Netherlands, Italy and Belgium. In the context of a Ricardian model of trade, this suggests that the welfare gains from trade in these countries will be smaller than in Austria, Germany, the Netherlands, and Spain.

²⁰ Similar conclusions can be inferred if we instead present mean values of the trade elasticities that are in between the 25 and 75 percentiles or in between the 10 and 90 percentiles.

²¹ This result is caused by a relatively large positive, but not statistically significant, coefficient found for the French dummy variable that interacts with the normalized region-sector's own trade share.

²² However, its median values can be found in Table B.2 of Appendix B.

For instance, the welfare gains from trade in Spain will be 62 percent larger than in Portugal using a Ricardian model of trade. Interestingly, we find that the sectoral heterogeneity in trade elasticities is much more important than the geographical heterogeneity at the country level, which is an expected result as we are using the median value of the trades elasticities of different sectors.²³

Finally, [Figure 2](#) depicts the regional trade elasticities. While previous studies have shown that the trade elasticities differ considerably across products and sectors (see, e.g., [Fontagné et al. 2022](#)), this figure clearly indicates that trade elasticities differ considerably across European regions. In general, our trade elasticities vary significantly within each country. Country by country, the regions that have a higher trade elasticity are the following: Wien in Austria (5.26), Bruxelles in Belgium (10.38), Berlin in Germany (8.11), Madrid in Spain (5.87), Lazio in Italy (9.72), Utrecht in The Netherlands (8.39), Algarve in Portugal (8.92) and Mellersta Norrland in Sweden (7.03). Thus, regions with better infrastructure, capital regions, urban and metropolitan areas or closer to trade hubs present higher trade elasticities compared to remote or less connected regions. The welfare gains from trade in these regions will be smaller than in other regions of their own countries. Our empirical approach finds elasticities for several Austrian regions that are roughly half the size of the trade elasticities found for many Italian and Portuguese regions. Thus, our estimates double the measured welfare gains from trade in these Austrian regions relative to most Italian and Portuguese regions.

[Insert Figure 2 here]

4.3. Overall productivity effects attributable to embeddedness

In this subsection, we examine the overall effect on measured TFP attributable to more embeddedness, an inverse of trade openness. [Carrascal-Incera and Orea \(2024\)](#) shows that, if we use a Markov process to model fundamental productivity, the elasticity of measured TFP with respect to a common increase in actual and lagged degrees of embeddedness is simply $\hat{\beta}\gamma_{nt}^j - 1/\hat{\theta}_{nt}^j$, where $\hat{\beta} = \hat{\rho}_\pi$ is the coefficient of lagged degree of embeddedness if we do not take into account the autoregressive persistence in productivity.²⁴ The first component of this elasticity measures the so-called *efficiency effect* and the second one measures the *selection effect* coined by [Caliendo et al. \(2018\)](#). Note that, as the selection effect on measured productivity tends to offset the efficiency effect in the above equation, the overall effect attributable to the degree of embeddedness is an empirical issue.

In Model D, $\hat{\beta}$ is common to all regions and sectors and it is close to 0.167. We thus find that, on average, regions would benefit from increasing their level of embeddedness because this would induce gains in their fundamental productivity. However, as the range of values of γ_n^j goes from 0.5% to 88%, the induced productivity gains would vary notably across sectors. As shown in [Table D.1](#) in [Appendix D](#), we would expect larger efficiency effects in

²³ Our previous findings also remain the same if our models address spatial autocorrelation in the error terms. This is an expected result because the error term (ε_{nt}^j) in both equations (5) and (7) includes spatial lags of fundamental productivity measurement errors (Wz_{nt-1}^j). For comparison grounds, the parameter estimates of both Model D (our more comprehensive specification) and a spatial error specification of this model are shown in [Table C.1](#) of [Appendix C](#). Note that the coefficient of $W\varepsilon_{nt}^j$ in the specification that includes spatial lagged error terms is significant but small. This explains why we find roughly the same parameter estimates regardless of whether we allow the error terms to be spatially correlated or not. The estimated trade elasticities are also highly correlated as the coefficient of correlation is slightly larger than 95% once we control for abnormal trade elasticities. In this appendix (see [Figure C.1](#)) we also replicate [Figure 1](#) but now using the parameter estimates of the spatial error Model D. As it is straightforward to notice, both figures are practically identical, indicating that our results in the main text are robust to this issue.

²⁴ $\hat{\beta} = \hat{\rho}_\pi = \hat{\rho}_\pi / (1 - \hat{\rho}_F)$ should be used if we consider the persistence of each region-sector's own fundamental productivity.

non-tradable sectors because the share of value added in gross output in these sectors (55%) almost doubles the share in tradable sectors (35%). In contrast, as $\hat{\theta}_{nt}^j > 0$ in practically all sectors, the non-spatial short run selection effect caused by a larger share of purchases from home is negative. As the sectoral trade elasticities for the non-tradable sectors are, on average, smaller than for the tradable sectors, we would also expect larger selection effects on measured TFP in non-tradable sectors. Figure 3 depict the *non-spatial* overall or net effect of embeddedness on measured TFP by sector and country taking into account or not the persistence of region-sector's own fundamental productivity (i.e., using short and long-run selection effects). The left panel a) of Figure 3 shows that the sector median selection effects on measured productivity tends to offset the efficiency effects in the short run. The left panel b) of Figure 3 shows that in the long run the efficiency effect is larger producing positive net effects for most sectors (except for Construction, Information, Real Estate and Professional activities).²⁵ The right panels of Figure 3 shows the country median productivity effects attributable to embeddedness. In the short run we find that the degree of embeddedness tends to reduce regions' measured productivity. The TFP deterioration is especially important in Austria and Spain. Interestingly, the long-run TFP deteriorations attributable to larger degrees of embeddedness vanishes due to the efficiency effect increases in the long run, except in Austria and Spain as the overall effect would still be negative.

To further examine the overall productivity effect attributable to the degree of embeddedness using our sectorial and regional data, we account for the improvements due to the positive spatial spillovers received from other sectors and regions when increasing their fundamental productivity. In Figure 4, it can be seen that the improvements (both spatial and temporal due to the efficiency effect in the long run) are more diverse for sectors than for countries, and they are always positive and important enough not to be neglected in any case. The temporal effects related to the efficiency gains in the long term are associated with sectors that are value-added intensive, meaning that these sectors benefit to a greater extent from local knowledge spillovers and agglomeration effects related to the size of the local economy. Once the spatial improvement has been accounted for, the net effect of embeddedness is still negative in the short run. However, taking into account the temporal improvement, the net effect of embeddedness is positive for all the sectors in the long run with the exception of Professional Activities. (M-N). For this sector, this result suggests that the degree of embeddedness is too high, and it would be beneficial for the economies to reduce the local dependency and increase the amount of resources from other regions/countries to avoid the negative effects of lock-in. Tables D.1 and E.1 present these results in detail, showing the net effect of embeddedness obtained for the non-spatial specification and the improvements due to the temporal and spatial effects.

At the country level, Figure 4 shows little heterogeneity in the improvement effect. It can be observed, however, that they are all positive and significant and that, in general, the peripheral countries and countries with larger shares of value-added (in this case, Spain, Sweden and Austria) benefit more from the spatial and temporal improvement than countries that are central and more reliant on sectors intensive in intermediate inputs (such as Belgium, France and Germany). These results can be seen in detail in Tables D.2 and E.2.

Nevertheless, when we analyse the net effects of embeddedness at the regional (subnational) level, we see much more diverse results. In Figure 5, it can be clearly seen that once we account for the selection effect (negative), the short run efficiency effect (positive), the temporal improvement of the efficiency effect in the long run (positive) and the spatial effect from improvements of fundamental productivity in other regions (positive), the results are quite heterogeneous. The regions that have a larger net effect of embeddedness are again

²⁵ The sectorial results are depicted in detail in Table D.1 in Appendix D. Figure D.1 in this appendix depicts the overall effects of embeddedness on measured TFP of each sector by country.

those that are capital regions and urban and metropolitan areas supporting the existence of agglomeration effects and local *activity-complex* externalities (Parr, 2002; Parr et al. 2002) during the period analysed. In general, it can be concluded that Italian regions would benefit from increasing their local dependency, as occurs with Swedish, North Portuguese and Dutch regions. Conversely, Austrian regions are practically unable to compensate the negative effects of the selection effect and should try to rely less on their own resources and increase their participation in trade value chains. Similar conclusions can be drawn for most Spanish, German and Belgian regions. Figure 6 shows the spatial improvement effects at the regional level. The regions that benefit more from other regions when increasing their fundamental productivity are those in the periphery (except for most Portuguese regions) and capital and urban regions (including Lisbon). These regions are more specialized in value-added intensive sectors, and increases in the fundamental productivity of other regions therefore have a stronger propagation effect in the trade network, captured by the commercial distances of our W matrix.

Finally, if we analyse these results and compare them with the level of GDP per capita of each region in 2010, we obtain a positive association, meaning that richer regions are the ones presenting higher net effects of the degree of embeddedness, though only for certain countries. We find a positive relationship (taking into account spatial effects in the long run) for regions in Austria (with a correlation coefficient of 0.69), in Belgium (0.88) and a weaker association in German (0.47) and Italian regions (0.46). At the same time, for Portugal we find a negative relationship (-0.80), and for the rest of the regions in Spain, the Netherlands and Sweden we find no statistically significant relationship. This is important when designing policies that try to account for interregional inequalities within countries and development traps. These results suggest that, if the richer regions are the ones benefiting more from the effects of embeddedness, implementing policies for increasing the participation in trade networks could reduce inequalities, as in the case of Austria or Belgium.

5. Conclusions

Regional productive embeddedness can be defined as the proportion of intermediate economic activity taking place within a specific region. It can therefore be understood as the opposite of the degree of openness (the lower the degree of embeddedness, the more dependent on external resources for production), and it varies sector by sector for each region. The analysis of this variable seems crucial for explaining how regions integrate into global trade networks, revealing vulnerabilities to disruptions in supply chains.

When decomposing the determinants of embeddedness, trade elasticities appear as the moderating parameter. Therefore, the aim of this paper was to propose a new approach to estimating regional trade elasticities based on a production-based model combined with a proxy-variable method, while accounting for spatial spillovers. Estimating trade elasticities at this geographical level can help to capture heterogeneous responses to trade frictions within countries that would otherwise be neglected.

Although most of the related papers estimating trade elasticities are performed at the country level, the trade elasticities found in this analysis are in line with previous studies. Care must be taken when making comparisons with other estimations since, as Broda and Weinstein (2006) or Imbs and Mejean (2017) have highlighted, trade elasticities tend to increase when the level of the sectoral disaggregation of the analysis increases. In any case, following the review in Carrascal-Incera and Orea (2024) on country-level results for trade elasticities, our estimations for regional (subnational) trade elasticities fall within the range of previous studies, going from 4.09 for Tirol (AT33) to 10.38 for Bruxelles (BE10), having excluded French regions. In general, metropolitan regions with better infrastructure and the capital regions present higher trade elasticities compared to less-connected regions. In terms of sectors, our estimates show that tradable sectors (A and B-E) present a higher trade elasticity than non-tradables (from F to R-U) as expected, ranging from 2.33 for Professional Activities (M-N) to 20.04 for Agriculture (A).

Comparing the country estimations reviewed in [Carrascal-Incera and Orea \(2024\)](#), we find differences that we attribute to the greater specialization that regional economies present. As countries are more diverse than regions (even at this level of aggregation), not all regions participate in trade with products from every sector. Taking that into account, our production-based method offers higher values for trade elasticities in Agriculture, very similar values for the Industry and Manufacturing sectors, and a little bit smaller in some services sectors such as Real Estate and Professional Activities. These results follow a pattern where sectors that are more concentrated spatially (tradables) present larger elasticities than those sectors evenly distributed across the regions (non-tradables). The analysis performed in this paper confirms that the production-based methodology can be used as an alternative approach for estimating sectoral trade elasticities, but also heterogeneous regional trade elasticities. The recent availability of databases containing multiregional multisectoral trade flows makes this feasible, opening new possibilities.

Once trade elasticities are obtained by region and sector, we can analyse the effect of the degree of embeddedness for European regions. Our model allows us also to control for spatial spillovers and to distinguish between short-run and long-run effects. Previous literature on the matter finds inconclusive evidence depending on the scope of the analysis, but the most recent papers agree that it is positive for regions to rely more on local suppliers and customers during crises ([Kitsos et al. 2023](#)), with variations across sectors and territories ([Carrascal-Incera and Orea, 2024](#)). In this analysis, we find a positive relationship between the net effects of the degree of embeddedness (taking into account spatial effects in the long run) and income levels for regions in Austria and in Belgium and (to a lesser extent) in German and Italian regions. At the same time, for Portugal there is a negative relationship between income per capita and the effects of embeddedness. For the rest of the regions in Spain, the Netherlands and Sweden, we find no relationship. As in [Kitsos et al. \(2023\)](#), which finds that the effects of embeddedness on regional resistance are quite heterogeneous, our results in general suggest that there is a positive effect mainly for richer regions, although the association is not consistently significant across countries.

In terms of sectors, we differentiate between several effects that not only help to trace the final net effect of embeddedness (efficiency effect, selection effect, spatial improvement effect), but also shed some light on the previous analysis by regions. The selection effect is always negative and larger for the sectors that suffer more from possible lock-in effects (namely services sectors: L and M-N). These would benefit from reducing their degree of embeddedness and participating in trade networks to have access to cheaper intermediate inputs. For the efficiency effect, it is clear that the activity-complex economies and the agglomeration effects are positive and promote regional productivity. This is especially patent for Real estate (L), Non-Market services (O-Q) and Other Services (R-U), all of which are value added-intensive sectors. However, in the short run and before considering spatial effects, the selection effect offsets the efficiency effect and the net effect of embeddedness is found to be negative, particularly for the aforementioned services sectors. The exception is the primary sector (A), where increasing the within-region linkages between sectors and thereby reducing the outside dependency, is beneficial.

In the long run, the degree of embeddedness is positive for most of the sectors, since the efficiency effect increases its impact and partially compensates the negative selection effect. Tradable sectors (A and B-E), but also Non-Market Services and Other Services, have a clear positive effect of creating local ties that generates the positive domestic knowledge spillovers. This is in line with the results found in [Carrascal-Incera and Orea, \(2024\)](#) which [reveal](#) a positive effect of embeddedness on overall productivity in value added-intensive services sectors. However, the clear exception is Professional Activities (M-N), which even in the long run presents a large negative net effect, meaning that this sector is clearly facing lock-in effects of being too embedded. Regions and countries where this sector represents an important part of their economy are presumably the ones that have a lower (or even negative)

effect of the degree of embeddedness. Finally, the spatial improvement effect is always larger for those sectors with larger efficiency effects (L, O-Q and R-U), both in the short and long run, meaning that these sectors benefit more from the external knowledge spillovers arising from increases in the fundamental productivity of commercial partners. In line with previous studies such as [Tsiapa et al. \(2025\)](#), and [Liu and Sickles \(2024\)](#), we therefore obtain positive and significant productivity spillovers. As one of the novelties in our paper, estimating the net effects of embeddedness in the long run implies that we capture the effects to a fuller extent than studies dealing solely with short run non spatial effects.

Subnational regions show significant differences in economic structures and specialization patterns, which influence their participation in global value chains and their exposure to external shocks. Our findings could provide policymakers with a basis for designing targeted development and sectoral strategies, aligned with every regional context. The heterogeneity found in the results that we present allows individual policies to be tailored depending on the nature of the relationship of embeddedness with economic performance, as part of a smart specialization strategy ([Capello and Kroll, 2018](#)). Such strategies could include reducing over-specialization in sectors like Professional Activities (M-N), where embeddedness has a clear negative net effect, and promoting stronger local sectoral linkages in places and sectors where embeddedness is associated with positive outcomes, such as Agriculture (A), Real Estate (L), Non-Market Services (O-Q), and Other Services (R-U). Moreover, implementing structural reforms through improving infrastructure and connections to trade centres can improve the regional presence in global value chains, reducing the negative effect of the selection effect. To conclude, we believe that this research sheds some light on the factors behind Europe's stagnation in productivity and economic growth, offering potential answers to some of the unresolved questions on this issue.

Declaration of competing interest

No potential conflict of interest was reported by the authors.

Data availability

The dataset used in our paper was obtained from [Huang and Koutroumpis \(2023b\)](#), publicly available at <https://zenodo.org/records/7765776> in its version v11, released on May 7, 2024.

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Author contributions

All authors contributed to the study conception and design. Material preparation and data collection were performed by André Carrascal-Incera. Both authors collaborated to write the different versions of the manuscript. The empirical models were estimated by Luis Orea. All authors read and approved the final manuscript.

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References

- Álvarez, I. C., & Barbero, J. (2016). The public sector and convergence with spatial interdependence: empirical evidence from Spain. *Applied Economics*, 48(24), 2238-2252.
- Bolea, L., Duarte, R., Hewings, G. J., Jiménez, S., & Sánchez-Chóliz, J. (2022). The role of regions in global value chains: an analysis for the European Union. *Papers in Regional Science*, 101(4), 771-795.
- Bontadini, F., Corrado, C., Haskel, J., Iommi, M., & Jona-Lasinio, C. (2023). EUKLEMS & INTANProd: industry productivity accounts with intangibles. Sources of growth and productivity trends: methods and main measurement challenges, *Luiss Lab of European Economics*, Rome.
- Broda, C., & Weinstein, D. E. (2006). Globalization and the gains from variety. *The Quarterly Journal of Economics*, 121(2), 541-585.
- Caliendo, L., & Parro, F. (2015). Estimates of the trade and welfare effects of NAFTA. *The Review of Economic Studies*, 82(1), 1-44.
- Caliendo, L., Parro, F., Rossi-Hansberg, E., & 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.
- Capello, R., & Kroll, H. (2018). From theory to practice in smart specialization strategy: emerging limits and possible future trajectories. In *Regional Innovation Strategies 3 (RIS3)* (pp. 1-14). Routledge.
- Carrascal-Incera, A., & Orea, L. (2024). A new approach for estimating trade elasticities and measuring the productivity effects associated with trade. *Economic Modelling*, 141, 106909.
- Carrascal-Incera, A., Liu, W., Orea, L., & Sickles, R. C. (2025). Beyond borders: how spillovers and commercial networks shape European productivity. *Journal of Productivity Analysis*, 1-49.
- Chen, W., Los, B., McCann, P., Ortega-Argilés, R., Thissen, M., & Van Oort, F. (2018). The continental divide? Economic exposure to Brexit in regions and countries on both sides of The Channel. *Papers in regional science*, 97(1), 25-55.
- Doraszelski, U., & Jaumandreu, J. (2013). R&D and productivity: Estimating endogenous productivity. *Review of Economic Studies*, 80(4), 1338-1383.
- Eaton, J., & Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5), 1741-1779.
- Escribá-Pérez, F. J., Gómez-Tello, A., Murgui-García, M. J., & Sanchis-Llopis, M. T. (2019). BD. EURS (NACE Rev. 2) database: New estimations. *Documento de Trabajo D-2019*, 1.
- Escriba, J., & Murgui, M. J. (2014). La base de datos BD. EURS (NACE Rev. 1). *Investigaciones Regionales-Journal of Regional Research*, (28), 173-194.
- Ferraresi, T., Ghezzi, L., Vanni, F., Caiani, A., Guerini, M., Lamperti, F., ... & Roventini, A. (2024). On the employment and health impact of the COVID-19 shock on Italian regions: a value chain approach. *Regional Studies*, 58(3), 490-506.
- Fontagné, L., Guimbard, H., & Orefice, G. (2022). Tariff-based product-level trade elasticities. *Journal of International Economics*, 137, 103593.

- Gandhi, A., Navarro, S., & Rivers, D. A. (2020). On the identification of gross output production functions. *Journal of Political Economy*, 128(8), 2973-3016.
- Gong, B., & Sickles, R. C. (2020). Non-structural and structural models in productivity analysis: study of the British Isles during the 2007–2009 financial crisis. *Journal of Productivity Analysis*, 53(2), 243-263.
- Han, J., & Sickles, R. C. (2024). Estimation of industry-level productivity with cross-sectional dependence by using spatial analysis. *Journal of Productivity Analysis*, 62(1), 29-52.
- Hang, J., Krishna, P., & Tang, H. (2020). Input-output networks and misallocation (No. w27983). National Bureau of Economic Research.
- Hou, Z., Kumbhakar, S. C., & Zhao, S. (2024). Productivity and efficiency: Do we need a bridge? *International Journal of Production Economics*, 274, 109287.
- Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly Journal of Economics*, 124(4), 1403-1448.
- Huang, S., & Koutroumpis, P. (2023a). European multi regional input output data for 2008–2018. *Scientific data*, 10(1), 218.
- Huang, S., & Koutroumpis, P. (2023b). European Multi Regional Input Output Data for 2008–2018, Database. *Zenodo*.
- Imbs, J., & Mejean, I. (2017). Trade elasticities. *Review of International Economics*, 25(2), 383-402.
- Jones, C. I. (2011). Intermediate goods and weak links in the theory of economic development. *American Economic Journal: Macroeconomics*, 3(2), 1-28.
- Kitsos, T. (2020). Economic resilience in Great Britain: An empirical analysis at the local authority district level. In *Handbook on regional economic resilience* (pp. 190-207). Edward Elgar Publishing.
- Kitsos, T., Grabner, S. M., & Carrascal-Incera, A. (2023). Industrial embeddedness and regional economic resistance in Europe. *Economic Geography*, 99(3), 227-252.
- LeSage, J. P., & Pace, R. K. (2014). The biggest myth in spatial econometrics. *Econometrics*, 2(4), 217-249.
- LeSage, J., & Pace, R. K. (2009). *Introduction to spatial econometrics*. Chapman and Hall/CRC.
- Liu, W., & Cheng, Q. (2021). Global production network, technology spillover, and shock transmission. *Applied Economics*, 53(60), 7020-7036.
- Liu, W., & Sickles, R. C. (2024). Industry-specific productivity and spillovers through input–output linkages: evidence from Asia-Pacific value chain, *Review of Income and Wealth*, 70(2), 345-369.
- Liu, W., Sickles, R. C., & Zhao, Y. (2022). Measuring productivity growth and technology spillovers through global value chains: Analysis of a US–Sino decoupling. In *Essays in Honor of M. Hashem Pesaran: Prediction and Macro Modeling* (pp. 243-267). Emerald Publishing Limited.
- Los, B., McCann, P., Springford, J., & Thissen, M. (2017). The mismatch between local voting and the local economic consequences of Brexit. *Regional studies*, 51(5), 786-799.
- Malikov, E., & Zhao, S. (2023). On the estimation of cross-firm productivity spillovers with an application to fdi. *Review of Economics and Statistics*, 105(5), 1207-1223.
- Martin, R., & Sunley, P. (2015). On the notion of regional economic resilience: conceptualization and explanation. *Journal of economic geography*, 15(1), 1-42.

- McCann, P. (2020). Perceptions of regional inequality and the geography of discontent: Insights from the UK. *Regional Studies*, 54(2), 256-267.
- Parr, J. B. (2002). Agglomeration economies: ambiguities and confusions. *Environment and planning A*, 34(4), 717-731.
- Parr, J. B., Hewings, G. J., Sohn, J., & Nazara, S. (2002). Agglomeration and trade: some additional perspectives. *Regional Studies*, 36(6), 675-684.
- Prades, E., & Tello-Casas, P. (2020). Heterogeneidad en el impacto económico del COVID-19 entre regiones y países del área del Euro. *Boletín Económico/Banco de España*, 2/2020.
- Restuccia, D., & Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic Dynamics*, 11(4), 707-720.
- Santamaría, M., Ventura, J., & Yeşilbayraktar, U. (2023). Exploring European regional trade. *Journal of International Economics*, 146, 103747.
- Simonovska, I., & Waugh, M. E. (2014). The elasticity of trade: Estimates and evidence. *Journal of international Economics*, 92(1), 34-50.
- Skevas, I. (2020). Inference in the spatial autoregressive efficiency model with an application to Dutch dairy farms. *European Journal of Operational Research*, 283(1), 356-364.
- Speth, D., Sauter, V., Plötz, P., & Signer, T. (2022). Synthetic European road freight transport flow data. *Data in brief*, 40, 107786.
- Thissen, M., Lankhuizen, M., van Oort, F., Los, B., & 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*
- Tsiapa M, Tzeremes PG, & Tzeremes NG (2025) Productivity slowdown and regional productivity heterogeneity. *Journal of Productivity Analysis*. <https://doi.org/10.1007/s11123-025-00751-9>.
- 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, 21–334.

Table 1. Descriptive Statistics

Type	Description	Units	Obs.	Mean	St. Dev.	Min	Max
<i>Output</i>							
	Y=gross output ^(a)	Millions of 2010 €	13200	18797	37703	109	594795
	V=value added ^(a)	Millions of 2010 €	13200	9370	17239	3	217663
<i>Inputs</i>							
	L=labour ^(b)	Thousands of persons	13200	110	200	0	2417
	K=capital ^(c)	Millions of 2010 €	13200	24955	75605	42	1637779
	M=materials ^(a)	Millions of 2010 €	13200	9426	22217	49	377132
<i>Other variables</i>							
	γ =value added/gross output	Percentage	13200	0.51	0.16	0	0.88
	Density=Population/land	Persons/Km ²	13200	378	848	3	6957

Sources: (a) [Huang and Koutoumpis \(2023a\)](#), European multi regional input output data for 2008-2018, Nature (Scientific Data). (b) Eurostat, Labour Force Survey. (c) Own estimation based on EUKLEMS & INTANProd (2023 release) and BD EURS.

Table 2. Parameter estimates. Homogeneous trade elasticity.

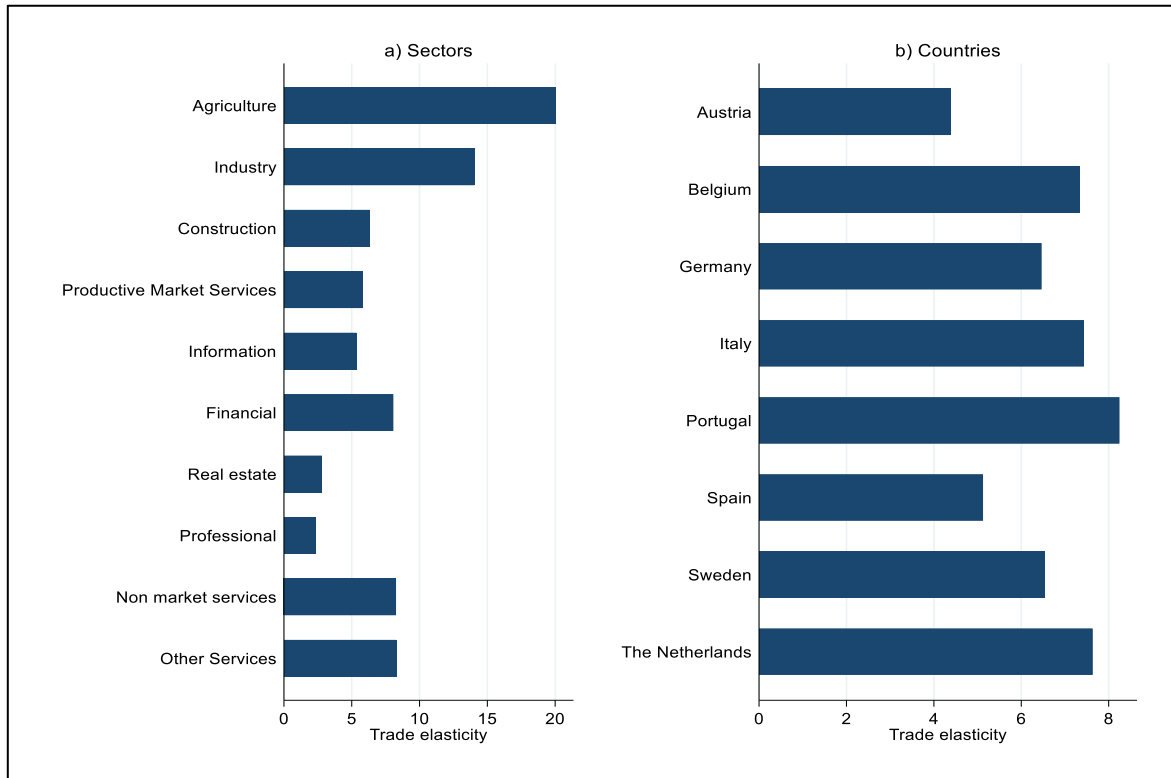
	Model 1			Model 2			Model 3			Model 4		
	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.
<i>Production function</i>												
$\ln(K/L)_t$	0.855	***	0.004	0.405	***	0.010	0.629	***	0.012	0.629	***	0.012
$1/2\ln(K/L)_t^2$				0.063	***	0.001	0.055	***	0.001	0.055	***	0.001
t	-0.003	**	0.002	-0.003	**	0.001	-0.006	**	0.003	-0.007	**	0.003
$1/2t^2$	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000
$\ln(K/L)_t \cdot t$							-0.028	***	0.001	-0.028	***	0.001
<i>Fundamental productivity</i>												
$\ln\pi_{t-1}$	0.027		0.025	-0.011		0.023	-0.021		0.022	-0.021		0.022
$\ln(V/L)_{t-1}$	0.519	***	0.012	0.502	***	0.011	0.510	***	0.011	0.510	***	0.011
$\ln(K/L)_{t-1}$	-0.481	***	0.013	-0.305	***	0.015	-0.438	***	0.015	-0.438	***	0.015
$1/2\ln(K/L)_{t-1}^2$				-0.021	***	0.001	-0.020	***	0.001	-0.020	***	0.001
$\ln(K/L)_{t-1} \cdot (t-1)$							0.028	***	0.001	0.028	***	0.001
<i>SLX variables</i>												
$W \cdot \ln(V/L)_{t-1}$	0.315	***	0.025	0.318	***	0.023	0.318	***	0.023	0.320	***	0.023
$W \cdot \ln(K/L)_{t-1}$	-0.264	***	0.026	-0.061	*	0.036	-0.057		0.035	-0.058	*	0.035
$W \cdot 1/2\ln(K/L)_{t-1}^2$				-0.027	***	0.004	-0.028	***	0.004	-0.028	***	0.004
$W \cdot \ln(K/L)_{t-1} \cdot (t-1)$							0.001	**	0.001	0.001	**	0.001
<i>Trade elasticity</i> ^(a)												
Intercept	-0.007	***	0.001	-0.007	***	0.001	-0.007	***	0.001	-0.007	***	0.001
t										0.001		0.000
Individual effects			Yes			Yes			Yes			Yes
<i>Trade elasticity</i>												
Sector-specific effects			No			No			No			No
Country-specific effects			No			No			No			No
Log likelihood			9559.8			10685.5			11099.2			11100.2
Obs.			120000			120000			120000			120000

Notes: * Significant at 10%, ** significant at 5%, *** significant at 1%. (a) Estimated coefficient for the normalized region-sector's own trade share ($\ln\pi_{nt}^i/\gamma_{nt}^i$) and its interaction with the time trend.

Table 3. Parameter estimates. Heterogeneous trade elasticity.

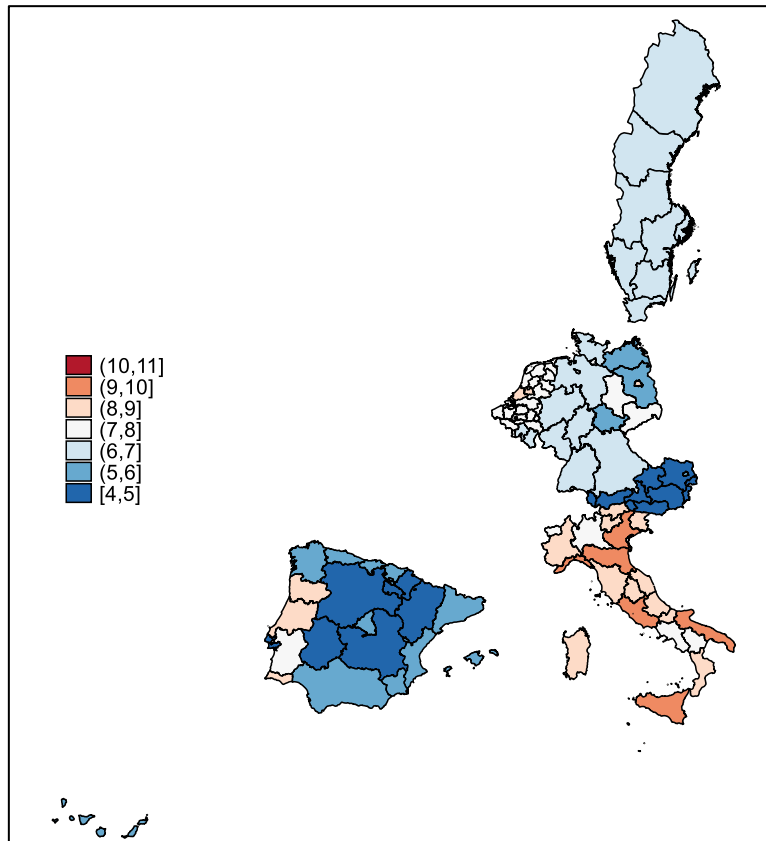
	Model A			Model B			Model C			Model D		
	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.
<i>Production function</i>												
$\ln(K/L)_t$	0.630	***	0.012	0.627	***	0.012	0.628	***	0.012	0.628	***	0.012
$1/2\ln(K/L)_t^2$	0.055	***	0.001	0.055	***	0.001	0.055	***	0.001	0.055	***	0.001
t	-0.007	**	0.003	-0.006	**	0.003	-0.006	**	0.003	-0.006	**	0.003
$1/2t^2$	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000
$\ln(K/L)_t \cdot t$	-0.028	***	0.001	-0.028	***	0.001	-0.028	***	0.001	-0.028	***	0.001
<i>Fundamental productivity</i>												
$\ln\pi_{t-1}$	0.131	***	0.023	0.158	***	0.023	0.167	***	0.023	0.167	***	0.023
$\ln(V/L)_{t-1}$	0.503	***	0.011	0.503	***	0.011	0.502	***	0.011	0.507	***	0.011
$\ln(K/L)_{t-1}$	-0.438	***	0.015	-0.438	***	0.015	-0.438	***	0.015	-0.443	***	0.015
$1/2\ln(K/L)_{t-1}^2$	-0.019	***	0.001	-0.019	***	0.001	-0.019	***	0.001	-0.019	***	0.001
$\ln(K/L)_{t-1} \cdot (t-1)$	0.028	***	0.001	0.028	***	0.001	0.028	***	0.001	0.028	***	0.001
<u>SLX variables</u>												
$W \cdot \ln(V/L)_{t-1}$	0.319	***	0.023	0.317	***	0.023	0.317	***	0.023	0.313	***	0.023
$W \cdot \ln(K/L)_{t-1}$	-0.059	*	0.034	-0.061	*	0.034	-0.062	*	0.034	-0.059	*	0.034
$W \cdot 1/2\ln(K/L)_{t-1}^2$	-0.028	***	0.004	-0.028	***	0.004	-0.028	***	0.004	-0.028	***	0.004
$W \cdot \ln(K/L)_{t-1} \cdot (t-1)$	0.001	**	0.000	0.001	**	0.000	0.001	**	0.000	0.001	**	0.000
<i>Trade elasticity</i>												
t	0.000		0.000	0.000		0.000	0.000		0.000	0.000		0.000
SD_{VA}							0.890	***	0.299	0.817	***	0.300
SD_{π}							-0.405		0.270	-0.305		0.272
$\ln(\text{Density})_t$										0.013	***	0.004
Individual effects			Yes			Yes			Yes			Yes
<i>Trade elasticity</i>												
Sector-specific effects			Yes			Yes			Yes			Yes
Country-specific effects			No			Yes			Yes			Yes
Log likelihood			11425.1			11448.4			11452.9			11457.2
Obs.			120000			120000			120000			120000

Figure 1. Trade elasticities by sector and country.



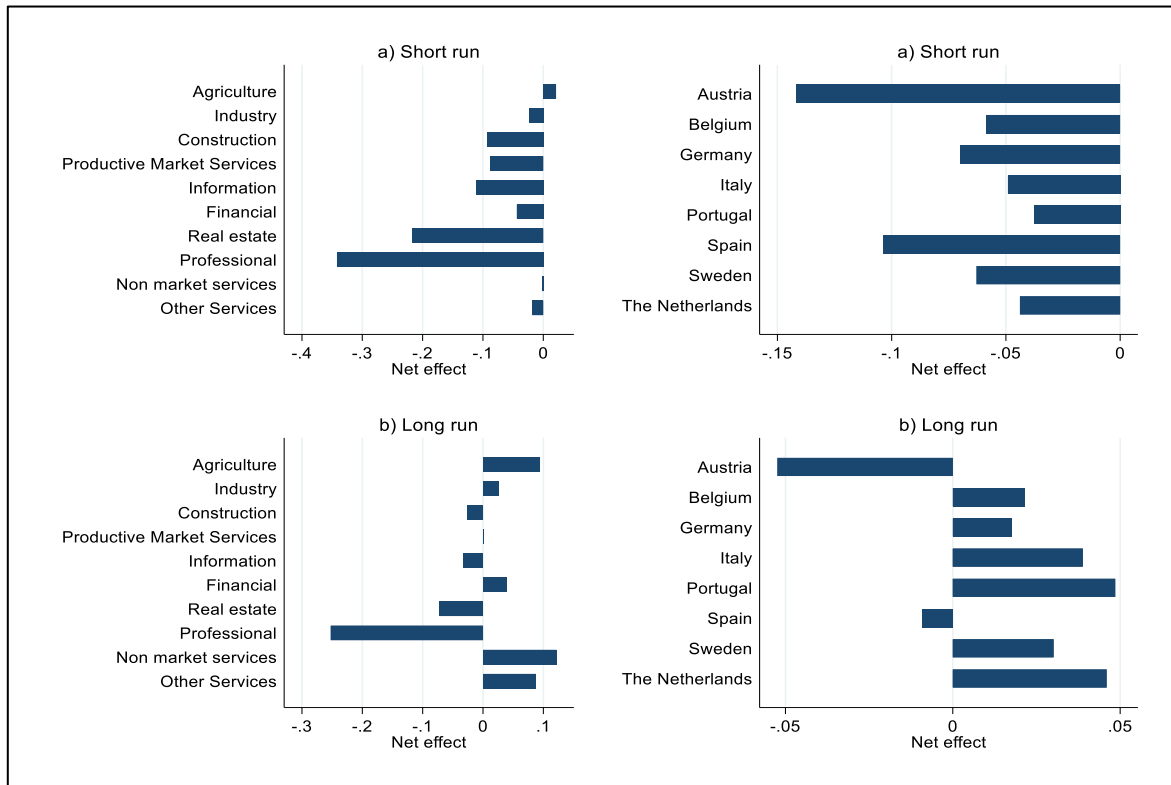
Note: Median values of each group. France is not depicted for presentation purposes

Figure 2. Regional trade elasticities.



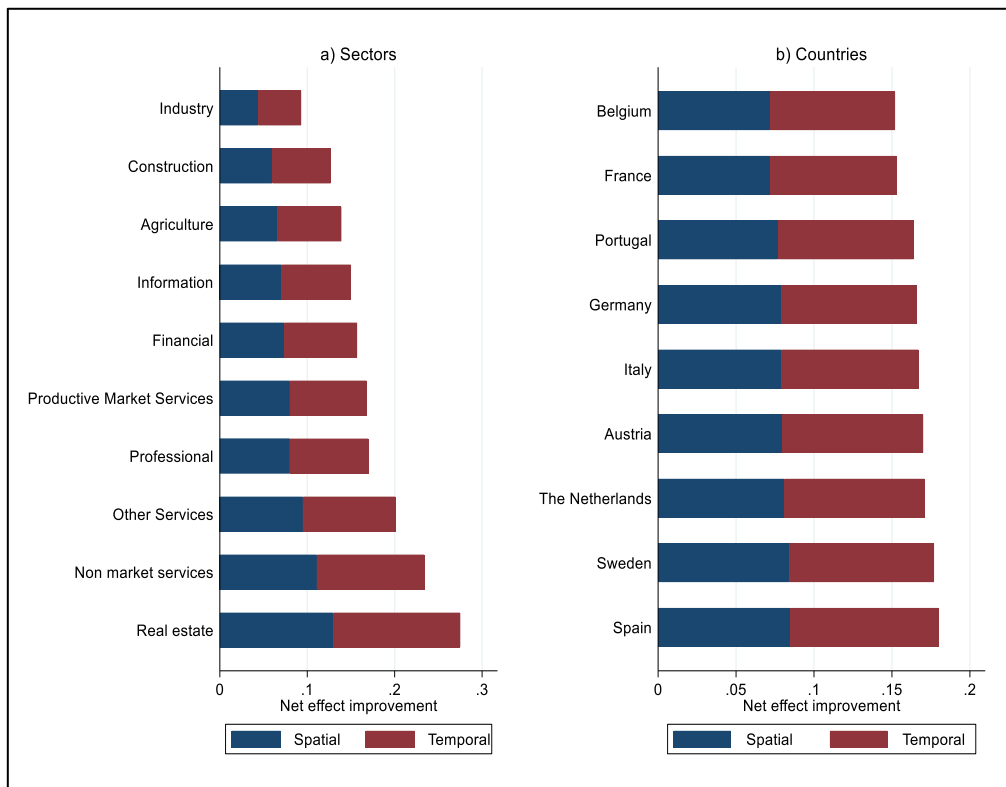
Note: Median values. France is not depicted for presentation purposes

Figure 3. Overall TFP effects attributable to embeddedness by sector and country.



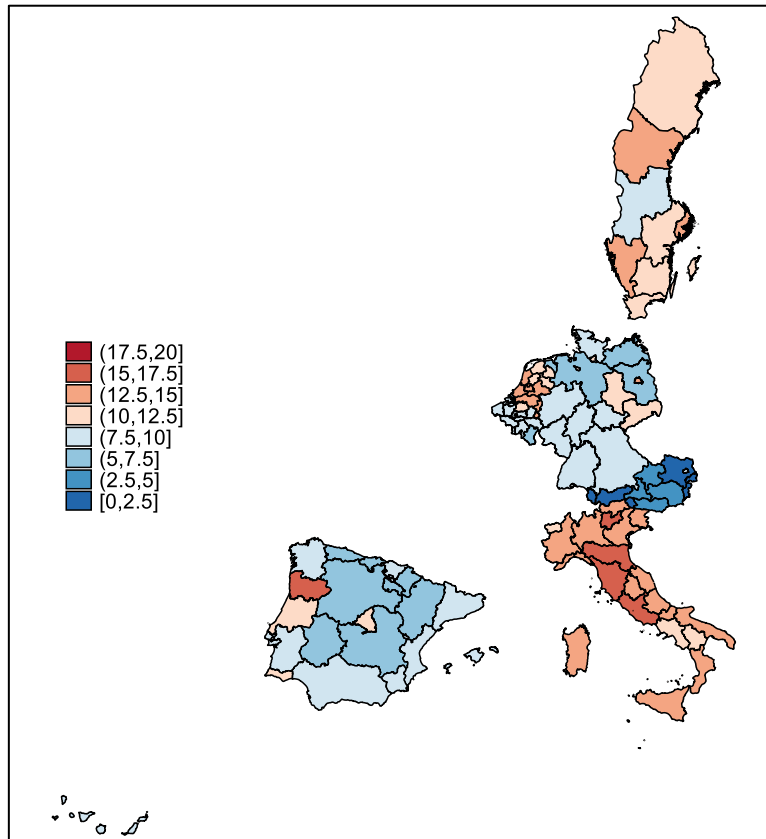
Note: Median values of each group. Non-spatial effects. France is not depicted for presentation purposes

Figure 4. Spatial and temporal contributions to the TFP effects attributable to embeddedness.



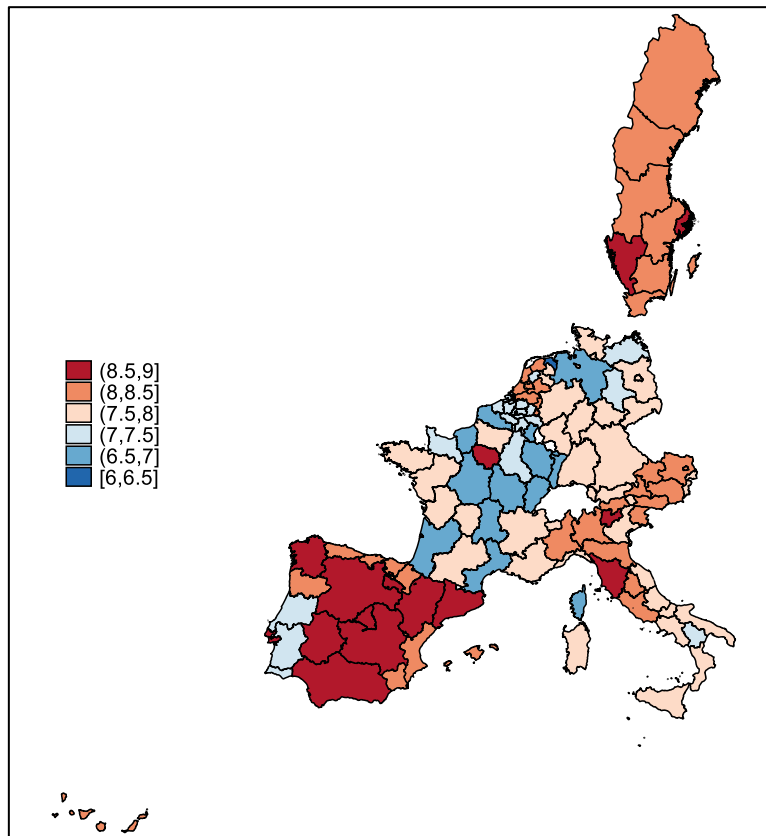
Note: the temporal improvement is computed as the difference between long and short-run non-spatial overall effects. The spatial improvement is then computed as the difference between spatial and non-spatial long-run overall effects.

Figure 5. Regional TFP effects attributable to embeddedness.



Note: median values using the spatial long-run efficiency effect. France is not depicted for presentation purposes

Figure 6. Spatial contribution to the TFP effects attributable to embeddedness.



Note: Median values of the difference between spatial and non-spatial long-run overall effect.

Appendix A. Data

Table A.1. List of regions

European regions

Austria	Belgium	Germany
Burgenland	AT11 Bruxelles	BE10 Baden-Württemberg
Niederösterreich	AT12 Antwerpen	BE21 Bayern
Wien	AT13 Limburg	BE22 Berlin
Kärnten	AT21 Oost-Vlaanderen	BE23 Brandenburg
Steiermark	AT22 Vlaams-Brabant	BE24 Bremen
Oberösterreich	AT31 West-Vlaanderen	BE25 Hamburg
Salzburg	AT32 Brabant Wallon	BE31 Hessen
Tirol	AT33 Hainaut	BE32 Mecklenburg-Vorpommern
Vorarlberg	AT34 Liège	BE33 Niedersachsen
	Luxembourg	BE34 Nordrhein-Westfalen
	Namur	BE35 Rheinland-Pfalz
		Sachsen
		Sachsen-Anhalt
		Schleswig-Holstein
		Thüringen
		DE10
		DE20
		DE30
		DE40
		DE50
		DE60
		DE70
		DE80
		DE90
		DEA0
		DEB0
		DED0
		DEE0
		DEF0
		DEG0
Spain	France	Italy
Galicia	ES11 Île de France	FR10 Piemonte
Asturias	ES12 Centre	FRB0 Valle d'Aosta
Cantabria	ES13 Bourgogne	FRC1 Liguria
País Vasco	ES21 Franche-Comté	FRC2 Lombardia
Navarra	ES22 Basse-Normandie	FRD1 Abruzzo
La Rioja	ES23 Haute-Normandie	FRD2 Molise
Aragón	ES24 Nord - Pas-de-Calais	FRE1 Campania
Madrid	ES30 Picardie	FRE2 Puglia
Castilla la Mancha	ES41 Alsace	FRF1 Basilicata
Castilla León	ES42 Champagne-Ardenne	FRF2 Calabria
Extremadura	ES43 Lorraine	FRF3 Sicilia
Cataluña	ES51 Pays de la Loire	FRG0 Sardegna
Valencia	ES52 Bretagne	FRH0 Bolzano/Bozen
Baleares	ES53 Aquitaine	FRI1 Trento
Andalucía	ES61 Limousin	FRI2 Veneto
Murcia	ES62 Poitou-Charentes	FRI3 Friuli-Venezia Giulia
Cantabria	ES70 Languedoc-Roussillon	FRJ1 Emilia-Romagna
	Midi-Pyrénées	FRJ2 Toscana
	Auvergne	FRK1 Umbria
	Rhône-Alpes	FRK2 Marche
	Provence-Alpes-Côte d'Azur	FRL0 Lazio
	Corse	FRM0
		ITC1
		ITC2
		ITC3
		ITC4
		ITF1
		ITF2
		ITF3
		ITF4
		ITF5
		ITF6
		ITG1
		ITG2
		ITH1
		ITH2
		ITH3
		ITH4
		ITH5
		ITI1
		ITI2
		ITI3
		ITI4
The Netherlands	Portugal	Sweden
Groningen	NL11 Norte	PT11 Stockholm
Friesland	NL12 Algarve	PT15 Östra Mellansverige
Drenthe	NL13 Centro	PT16 Småland med öarna
Overijssel	NL21 Lisboa	PT17 Sydsverige
Gelderland	NL22 Alentejo	PT18 Västsverige
Flevoland	NL23	Norra Mellansverige
Utrecht	NL31	Mellersta Norrland
Noord-Holland	NL32	Övre Norrland
Zuid-Holland	NL33	
Zeeland	NL34	
Noord-Brabant	NL41	
Limburg	NL42	
		SE11
		SE12
		SE21
		SE22
		SE23
		SE31
		SE32
		SE33

Note: Regions ordered using their code.

Table A.2. List of sectors.

ID	Code	Name	Description
A	1	Agriculture	Agriculture, forestry and fishing (A)
B-E	2	Industry	Extractive industries (B); Manufactures (C); Energy (D) and water supply (E)
F	3	Construction	Construction (F)
G-I	4	Productive Market Services	Wholesale and retail trade; repair of motor vehicles (G); Transport and storage (H) and Hotels and restaurants (I)
J	5	Information	Information and communication (J)
K	6	Financial	Financial and insurance activities (K)
L	7	Real estate	Real estate activities (L)
M_ N	8	Professional	Professional, scientific and technical activities (M); Administrative and support service activities (N)
O-Q	9	Nonmarket services	Public administration and defence; compulsory social security (O); Education (P); Health and social work (Q)
R-U	10	Other Services	Art, entertainment and recreation (R); Other services (S); Activities of households (T); Extra-territorial organizations and bodies (U)

Appendix B. Trade elasticities

Table B.1. Trade elasticities by sector.

ID	Code	Sector	Model A	Model B	Model C	Model D
A	1	Agriculture	394.9	-10.8	45.2	20.04
B-E	2	Industry	26.6	22.3	17.9	14.03
F	3	Construction	6.06	6.20	6.5	6.33
G-I	4	Productive Market Services	6.28	5.91	5.76	5.77
J	5	Information	6.08	6.05	5.8	5.3
K	6	Financial	23.9	17.0	8.26	8.06
L	7	Real estate	2.73	2.70	2.89	2.80
M_N	8	Professional	2.31	2.26	2.30	2.33
O-Q	9	Non-market services	9.47	10.0	8.7	8.27
R-U	10	Other Services	14.0	10.5	8.75	8.27

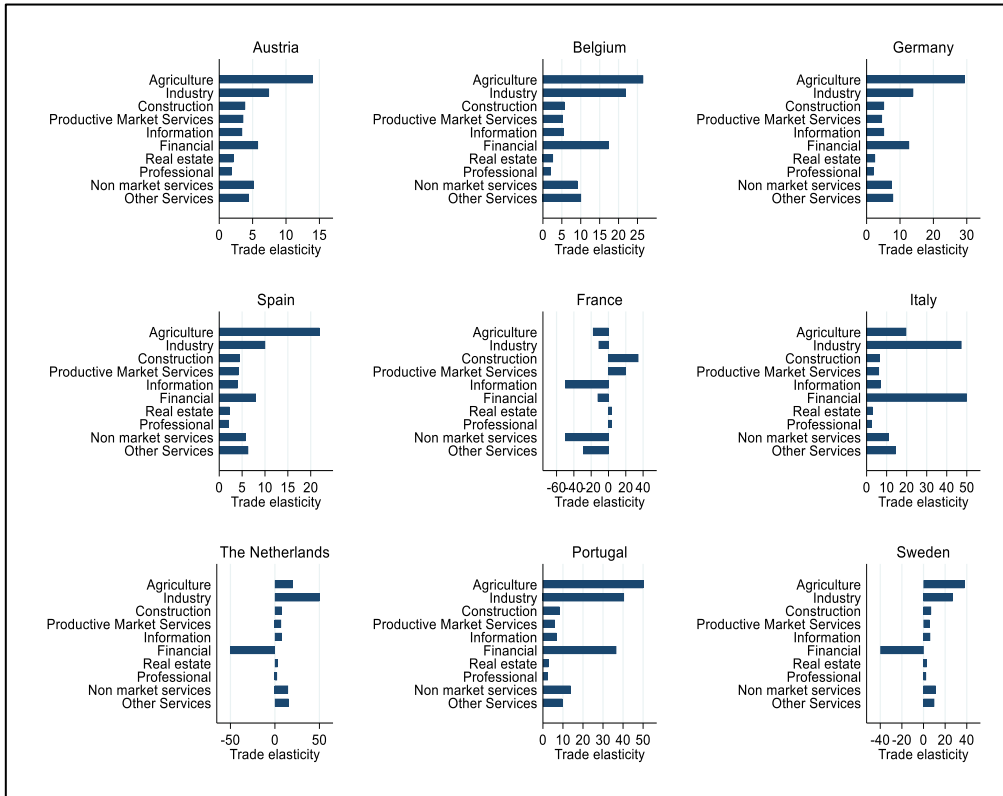
Note: Median values of each group.

Table B.2. Trade elasticities by country.

Code	Sector	Model A	Model B	Model C	Model D
AT	Austria	7.9	6.3	4.54	4.38
BE	Belgium	7.9	7.4	8.4	7.34
DE	Germany	7.9	7.3	7.3	6.46
ES	Spain	7.9	5.54	5.13	5.12
FR	France	7.9	7.4	-14.0	-11.8
IT	Italy	7.9	6.33	9.1	7.43
NL	Netherlands	7.9	6.62	7.46	7.63
PT	Portugal	7.9	7.1	7.7	8.24
SE	Sweden	7.9	5.93	6.2	6.53

Note: Median values of each group.

Figure B.1. Trade elasticities of each sector by country.



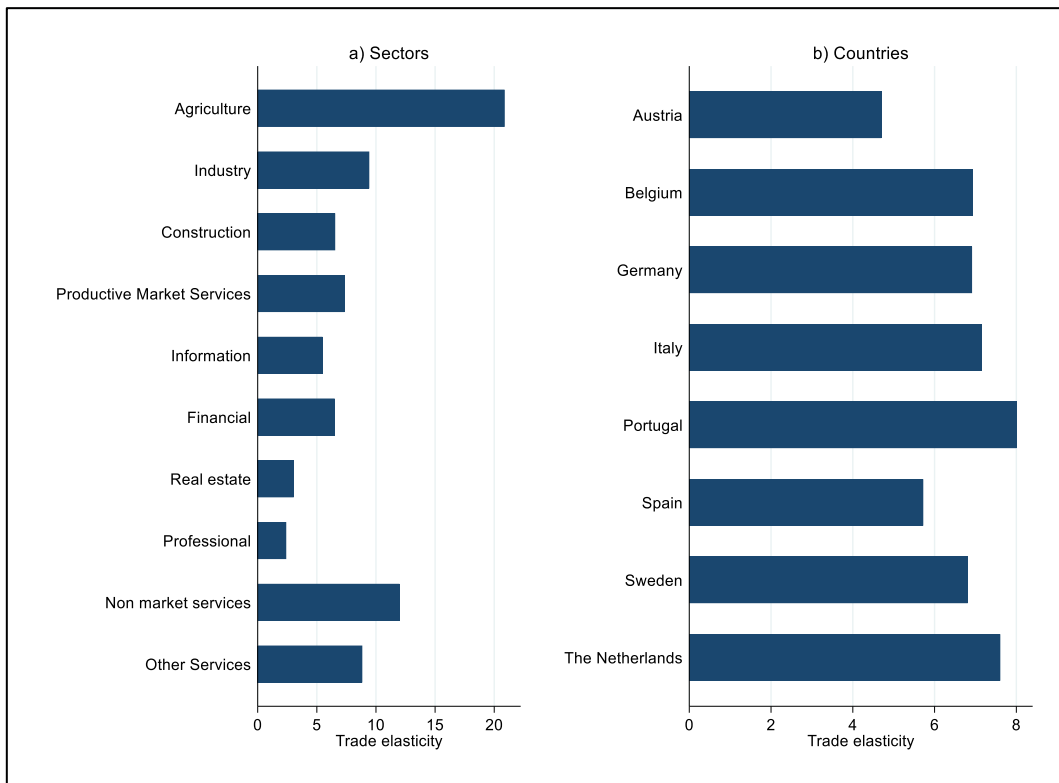
Note: Median values of each group. We truncated the values below -50 and above +50.

Appendix C. Spatial error model (SEM)

Table C.1. Parameter estimates of the spatial error model D.

	Non-spatial errors			Spatial errors		
	Coef.		s.e.	Coef.		s.e.
<i>Production function</i>						
$\ln(K/L)_t$	0.628	***	0.012	0.629	***	0.012
$1/2\ln(K/L)_t^2$	0.055	***	0.001	0.055	***	0.001
t	-0.006	**	0.003	-0.009	***	0.003
$1/2t^2$	0.000		0.000	0.000		0.000
$\ln(K/L)_t \cdot t$	-0.028	***	0.001	-0.028	***	0.001
<i>Fundamental productivity</i>						
$\ln\pi_{t-1}$	0.167	***	0.023	0.167	***	0.023
$\ln(V/L)_{t-1}$	0.507	***	0.011	0.507	***	0.011
$\ln(K/L)_{t-1}$	-0.443	***	0.015	-0.444	***	0.015
$1/2\ln(K/L)_{t-1}^2$	-0.019	***	0.001	-0.019	***	0.001
$\ln(K/L)_{t-1} \cdot (t-1)$	0.028	***	0.001	0.028	***	0.001
<u>SLX variables</u>						
$W\ln(V/L)_{t-1}$	0.313	***	0.023	0.282	***	0.025
$W\ln(K/L)_{t-1}$	-0.059	*	0.034	-0.043		0.037
$1/2W\ln(K/L)_{t-1}^2$	-0.028	***	0.004	-0.026	***	0.004
$W\ln(K/L)_{t-1} \cdot (t-1)$	0.001	**	0.000	0.002	***	0.001
<i>Trade elasticity</i>						
t	0.000		0.000	0.000		0.000
SD_{VA}	0.817	***	0.300	0.791	***	0.300
SD_{π}	-0.305		0.272	-0.250		0.272
$\ln(\text{Density})_t$	0.013	***	0.004	0.012	***	0.004
<i>Spatial error term</i>						
$W\varepsilon_t$				0.175	***	0.025
<i>Production function</i>						
Individual effects			Yes			Yes
<i>Trade elasticity</i>						
Sector-specific effects			Yes			Yes
Country-specific effects			Yes			Yes
Log likelihood			11457.2			11481.5
Obs.			120000			120000

Figure C.1. Trade elasticities by sector and country using a SEM.



Appendix D. TFP effects attributable to embeddedness

Table D.1. Overall effects of embeddedness by sector.

ID	Code	Sector	Value added share	Selection Effect	Short run		Long run	
					Efficiency Effect	Overall effect	Efficiency Effect	Overall effect
A	1	Agriculture	42.5	-0.050	0.071	0.021	0.144	0.094
B-E	2	Industry	28.6	-0.071	0.048	-0.023	0.097	0.026
F	3	Construction	38.7	-0.158	0.065	-0.093	0.132	-0.026
G-I	4	Productive Market Services	51.3	-0.173	0.086	-0.087	0.174	0.001
J	5	Information	45.8	-0.188	0.077	-0.111	0.156	-0.032
K	6	Financial	47.9	-0.124	0.080	-0.044	0.163	0.039
L	7	Real estate	84.0	-0.358	0.141	-0.217	0.286	-0.072
M_N	8	Professional	52.0	-0.429	0.087	-0.342	0.177	-0.252
O-Q	9	Non market services	71.2	-0.121	0.119	-0.002	0.242	0.121
R-U	10	Other Services	61.4	-0.121	0.103	-0.018	0.209	0.088

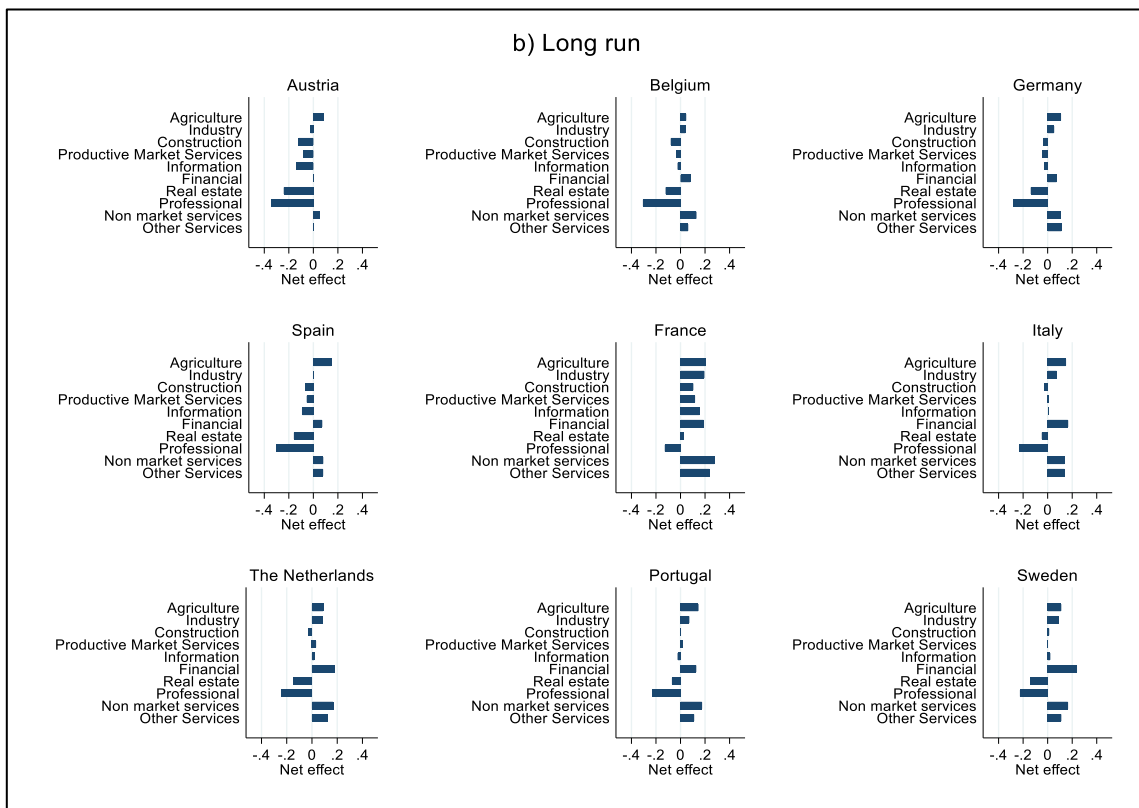
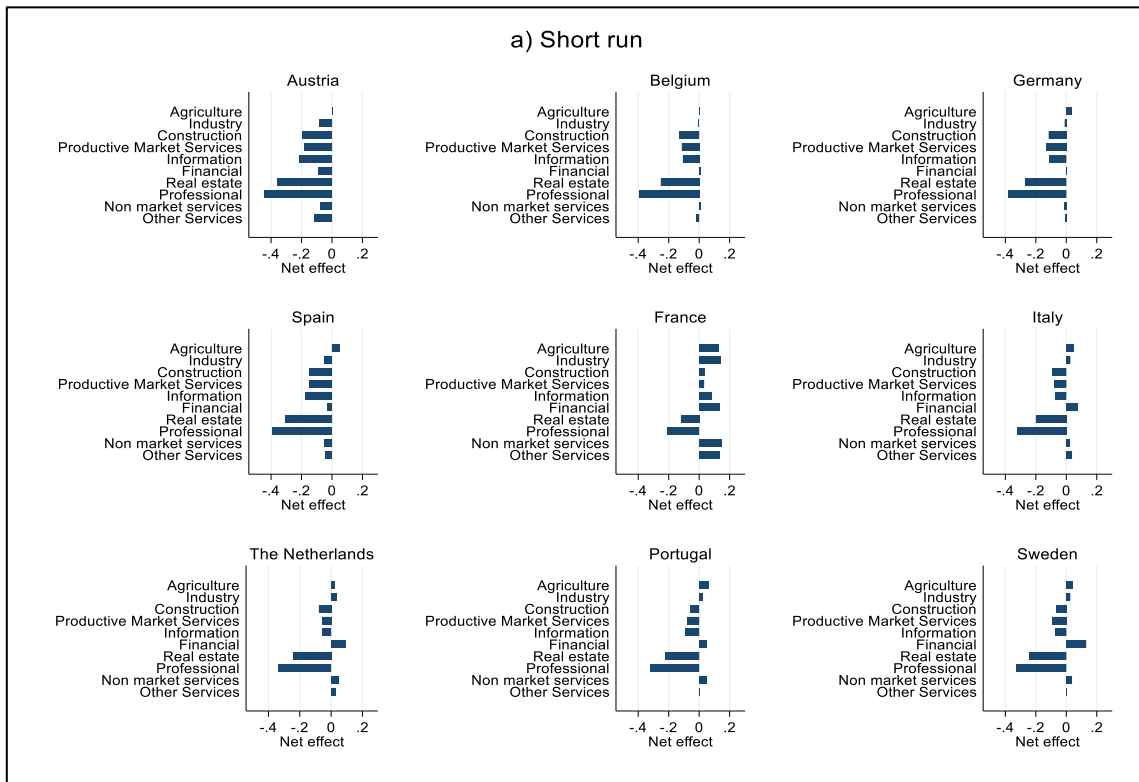
Note: Median values of each group.

Table D.2. Overall effects of embeddedness by country.

Code	Sector	Value added share	Selection Effect	Short run		Long run	
				Efficiency Effect	Overall effect	Efficiency Effect	Overall effect
AT	Austria	51.8	-0.228	0.087	-0.142	0.176	-0.052
BE	Belgium	46.4	-0.136	0.078	-0.059	0.158	0.021
DE	Germany	50.7	-0.155	0.085	-0.070	0.172	0.017
ES	Spain	54.7	-0.195	0.092	-0.104	0.186	-0.009
FR	France	46.7	0.085	0.078	0.163	0.159	0.244
IT	Italy	51.0	-0.135	0.085	-0.049	0.173	0.039
NL	Netherlands	52.1	-0.131	0.087	-0.044	0.177	0.046
PT	Portugal	50.0	-0.121	0.084	-0.038	0.170	0.049
SE	Sweden	53.9	-0.153	0.090	-0.063	0.183	0.030

Note: Median values of each group.

Figure D.1. Net effects of embeddedness of each sector by country.



Appendix E. Spatial contribution to the TFP effects attributable to embeddedness

Table E.1. Spatial long-run effects of embeddedness by sector.

Code	Sector	Short run			Long run		
		Non-spatial	+ improvement	= Spatial	Non-spatial	+ improvement	= Spatial
1	Agriculture	0.021	0.032	0.054	0.094	0.066	0.160
2	Industry	-0.023	0.022	-0.002	0.026	0.044	0.070
3	Construction Pr. Market	-0.093	0.030	-0.063	-0.026	0.060	0.034
4	Serv.	-0.087	0.039	-0.048	0.001	0.079	0.081
5	Information	-0.111	0.035	-0.076	-0.032	0.071	0.039
6	Financial	-0.044	0.037	-0.007	0.039	0.074	0.113
7	Real estate	-0.217	0.064	-0.153	-0.072	0.130	0.058
8	Professional	-0.342	0.040	-0.302	-0.252	0.081	-0.172
9	NM services	-0.002	0.054	0.053	0.121	0.110	0.232
10	Other Services	-0.018	0.047	0.029	0.088	0.095	0.183

Note: Median values of each group.

Table E.2. Spatial long-run effects of embeddedness by country.

Code	Country	Short run			Long run		
		Non-spatial	+ improvement	= Spatial	Non-spatial	+ improvement	= Spatial
AT	Austria	-0.142	0.040	-0.102	-0.052	0.080	0.028
BE	Belgium	-0.059	0.035	-0.023	0.021	0.072	0.093
DE	Germany	-0.070	0.039	-0.031	0.017	0.079	0.096
ES	Spain	-0.104	0.042	-0.062	-0.009	0.085	0.076
FR	France	0.163	0.036	0.199	0.244	0.072	0.316
IT	Italy	-0.049	0.039	-0.010	0.039	0.079	0.118
NL	Netherlands	-0.044	0.040	-0.004	0.046	0.081	0.127
PT	Portugal	-0.038	0.038	0.001	0.049	0.077	0.126
SE	Sweden	-0.063	0.041	-0.022	0.030	0.084	0.114

Note: Median values of each group.