NONPARAMETRIC SPATIAL FRONTIER MODELS FOR PRODUCTIVITY ANALYSIS: EVIDENCE FROM EU REGIONS

Camilla Mastromarco, Léopold Simar

LIDAM Discussion Paper ISBA
2025 / 20

UCLouvain

LIDAM
ISBA | Louvain Institute of Data Analysis and Modeling in economics and statistics

ISBA
Voie du Roman Pays 20 - L1.04.01
B-1348 Louvain-la-Neuve
Email : lidam-library@uclouvain.be
https://uclouvain.be/en/research-institutes/lidam/isba/publication

Nonparametric Spatial Frontier Models for Productivity Analysis: Evidence from EU Regions

Camilla Mastromarco[⋆] Léopold Simar[§]

November 13, 2025

Abstract: This paper proposes a novel nonparametric panel data framework for estimating conditional production frontiers and efficiency measures that explicitly accounts for spatial interdependencies. By integrating recent advances in nonparametric frontier estimation with spatial panel data analysis, the proposed approach offers a flexible and robust framework for assessing productivity and efficiency in the presence of spatial interactions, explicitly accounting for both global and local spatial effects. By extending recently developed tools for estimating Malmquist productivity indices to conditional nonparametric frontier efficiency models, we provide a refined decomposition of productivity growth into technological change, efficiency change, and scale effects within a fully nonparametric framework. Applying this framework to a comprehensive dataset on European regions, we provide new evidence on spatial patterns of productivity growth and efficiency dynamics across the EU. The results reveal marked heterogeneity in regional performance and highlight the crucial role of spatial spillovers in shaping productivity outcomes. Ignoring these interdependencies can lead to mismeasurement of productivity trends, reinforcing the value of our proposed spatial nonparametric frontier approach for policy and performance analysis.

JEL: C14, C13, C33, D24, O47.

Keywords: Nonparametric Conditional Frontier, Panel Data Model, Spatial Dependence, Productivity Analysis, Malmquist Productivity Index, EU Regional Performance.

[⋆] Dipartimento di Economia, Statistica e Finanza, Universitá degli Studi della Calabria. Via Pietro Bucci - 87036 Arcavacata di Rende, Cs, camilla.mastromarco@unical.it .

This paper is based on a plenary presentation I gave at the North American Productivity Workshop (NAPW XII) held at the Virginia Tech Research Center in Arlington Virginia in June 2025 honouring Léopold Simar who received a Lifetime Achievement Award.

[§]Institut de Statistique,Biostatistique et Sciences Actuarielles (ISBA), LIDAM, UCLouvain. Voie du Roman Pays 20 B - 1348 Louvain-La-Neuve - Belgium. Email: leopold.simar@uclouvain.be.

1 Introduction

The measurement of productivity and efficiency has long been a cornerstone of economic and managerial research, offering key insights into the performance of firms, industries, and regions. Over the past few decades, the development of nonparametric frontier models has greatly advanced this field by allowing for flexible and robust estimation of production frontiers and efficiency scores. However, traditional approaches often fail to adequately capture spatial dependencies, which play a crucial role in understanding efficiency dynamics across economic units.

As economic agents tend to be influenced by their neighbours in a rather complex manner, recent developments have generated a growing empirical literature on methods for modelling these interlinkages among units in datasets with a panel structure by taking into account spatial or cross-section correlation.[1] In this paper, we propose a novel nonparametric panel data framework that integrates recent advances in frontier estimation with spatial panel data analysis. The proposed approach allows for the estimation of conditional frontiers and efficiency measures while explicitly accounting for both global and local spatial interdependencies. Unlike conventional nonparametric frontier methods that assume independence across units, our approach considers the role of spatial spillovers and interactions in shaping productivity outcomes.

The issue of cross-sectional dependence (CSD) has been widely discussed in the panel data literature (Bai and Ng 2006, Pesaran 2006, Bai 2009, Kapetanios et al. 2011). Unobserved time-specific shocks can induce correlation across units, leading to biased estimates when ignored. The literature deals with cross section dependence, attributable to economy-wide shocks that affect all units in the cross section but with different intensities, by assuming a multi-factor error process characterized by a finite number of unobserved common factors.

In the context of productivity analysis, several studies have emphasized the importance of accounting for global shocks and business-cycle spillovers (Mastromarco et al. 2013, 2016a, Mastromarco and Simar 2018). These works demonstrate that globalization and cross-country interdependence are crucial for understanding productivity and output growth. Druska and Horrace (2004) are the first to develop a panel data efficiency frontier model with autoregressive spatial errors and apply the Schmidt and Sickles (1984) estimator to calculate firm-specific efficiency scores without imposing any distributional assumption on inefficiency terms. Schmidt et al. (2009) show that the failure to control for the presence of cross-sectional correlation in the regional production data, may yield biased results in both direct and indirect impacts of each explanatory variable. Glass et al. (2016) present a spatial autoregressive

[1] Two main approaches are proposed: the residual multifactor structure and the spatial econometric approach.

stochastic frontier model and propose a multi-stage pseudo MLE. Gude et al. (2018) extend this approach and develop a generalised spatial auoregressive stochastic frontier model with time-varying variables that influence the degree of the global spatial interaction. All these studies highlight that failure to account for the spatial dependence may result in biased estimates of efficiency scores. See also Gamerman and Moreira (2004).

Nonetheless, most attempts to incorporate global and local spatial effects into productivity and efficiency analysis remain within the parametric framework. The only exception is Mastromarco and Simar (2018), who propose a non parametric location-scale model to accommodate global factors in cross-country analysis of efficiency and productivity. Building on recent developments in conditional nonparametric frontiers, we propose a new approach that allows for both global (strong) and local (weak) spatial dependence within a panel data framework. Our model builds on the nonparametric, nonseparable frontier framework of Mastromarco et al. (2025), itself grounded in the econometric literature on nonseparable models (Matzkin 2003) and nonseparable triangular systems (Imbens and Newey 2009).

Conditional frontiers provide a flexible approach to account for the role of external variables (neither inputs nor outputs) in the production process. There are two main approaches. Direct approach which estimates non-parametrically conditional distribution functions and requires smoothing techniques and the use of selected bandwidths. However, this approach may suffer from some statistical instability due to the fact that when estimating the boundary of the distribution function, the bandwidths, usually computed by Least-Squares-Cross validation, may not be of optimal order (see Bădin et al. 2019). Hence we use an indirect and fully nonparametric approach (Mastromarco et al. 2025) which avoid the problem of estimating the bandwidths in the direct approach of conditional efficiency, by eliminating in a first step the influence of the external factors on the inputs and outputs. By doing this we produce "pure" inputs and outputs which allow to estimate a "pure" measure of efficiency, more reliable for ranking the units, since the influence of the external factors have been eliminated.

Output growth is typically explained as the accumulation of factor inputs and the growth of total factor productivity. This can be understood by viewing output growth from the perspective of a production possibility frontier, where production units operate either on or within the frontier, with the distance from the frontier representing inefficiency. A production unit's frontier can shift outward or inward over time (technological change), or a unit can move towards or away from the frontier (efficiency change). Moreover, a unit can move along the frontier by changing its input mix. Therefore, productivity growth can be decomposed into three components: technological change, efficiency change, and input variation, with the first two jointly representing productivity change. Starting with Färe et al. (1994), many studies have used methods based on Malmquist productivity indexes (Caves et al. 1982) to decompose productivity growth into components attributable to technological change, technological catch-up, and input accumulation, thereby linking the literature on convergence and the efficient frontier. To assess the forces behind output growth, we build on recent developments (Kneip et al. 2025) and estimate Malmquist productivity indices using “pure” inputs and outputs, decomposing productivity growth into technological change, efficiency change (technological catch-up), and scale effects.

The remainder of the paper is organized as follows. Section 2 presents the methodological framework and theoretical underpinnings. Section 3 describes the data, while Section 4 discusses the main findings and their implications for economic performance analysis. Section 5 concludes with remarks and directions for future research.

2 Model

We apply Mastromarco et al. (2025) methodology and consider a Data Generating Process (DGP) characterizing the production process in the presence of environmental factors and we adapt their models to a spatial and dynamic framework to allow the inclusion of global and local spatial factors and the estimation of Malmquist index. Consider a generic input vector $X \in \mathbb{R}_+^p$, a generic output vector $Y \in \mathbb{R}_+$ and we will denote by $Z \in \mathbb{R}^r$ the generic vector of environmental variables (local and global spatial factors, in our study). Since we are in a context of panel data, our sample will be denoted by (X_{it}, Y_{it}, Z_{it}), with $i = 1, \ldots, n$ being the unit index and $t = 1, \ldots, T$ the time index. To better investigate the influence of globalization factors (e.g., technological shocks and financial crises) and local spatial factors (technological productivity spillovers) on the economic performance of regions under analysis, we develop a method to envelop the effect of strong (global factors) and weak (local spatial factors) cross section dependence (CSD) on the production process.

Our approach allows to capture the technological change, efficiency change and scale change to the estimation of Malmquist productivity indices. Our method, differently from other studies, which apply Malmquist productivity indices, consents to take into account the effect of external variables. Since we include local and global spatial factors as external variables, this enables us to eliminate the spatial dependence, in a very flexible and robust way (fully non parametric model). Our pure efficiency measure provides a better indicator to assess the economic performance of production units over time and allows the ranking of production units facing different environmental factors at different time periods by taking into account also the spatial externalities in productivity. Hence, we assume that the production process is function of unobserved global time-varying factors and spatial local factors.

To capture local spatial factors, and hence, spatial spillovers in production, we calculate the term $Y^*_{it} = \sum_{j=1}^{N} w_{ij} Y_{jt}$ with w_{ij} being the (i,j)-th element of the spatial weighting matrix with the weights measure technological distance (see section Data for more details). Following Pesaran (2006) and Mastromarco and Simar (2018) we consider $F_t = (X_{\cdot t}, Y_{\cdot t})$ as proxy for the unobserved global factors associated with globalisation and the business-cycle.[2] These time factors capture the correlation among units; by eliminating the effect of these factors on production process we mitigate the problem of CSD.[3] We include also time trend to eliminate any long term pattern from our variables.

Econometric parametric techniques have been developed to separately address spatial and factor dependencies separately. Spatial endogeneity is tackled through methods such as quasi maximum likelihood (QML) or instrumental variables (IV) and generalized method of moments IV/GMM estimators, while common factors are approached via principal components (PC) estimates or the cross-sectional averages of variables. Recently, some progresses have been made in modelling both local and global cross-section correlations through the joint analysis of spatial- and factor-based panel data models. Mastromarco et al. (2016b) propose a technique for modelling stochastic frontier panels by combining the exogenous factor-based approach and an endogenous threshold selection mechanism. Bai and Li (2021) develops the QML estimation for a homogeneous spatial panel data model with common shocks. Yang (2021) develops a consistent estimator that combines the common correlated effects (CCE) and instrumental variable (IV) estimation. See also Shi and Lee (2017), Kuersteiner and Prucha (2020) and Lu (2022). Chen et al. (2022) develop the panel data model with the parameter heterogeneity that can accommodate both spatial dependence and common factors, and propose the CCEX-IV estimator that approximates factors by the cross-section averages of regressors.

To address both global and local dependence, we employ the indirect approach to nonparametric conditional frontier analysis introduced by Florens et al. (2014) and extended to the nonseparable case by Mastromarco et al. (2025), building on the framework of nonseparable triangular equations developed by Matzkin (2003) and Imbens and Newey (2009).

Consider a production setting where a single output $Y \in \mathbb{R}$ is generated from a vector of inputs $X \in \mathbb{R}^p$. We incorporate external variables $Z \in \mathbb{R}^k$, where Z denote observable factors that may affect the production process. Our goal is to explicitly account for the spatial components when estimating production frontiers and inefficiency.

We may consider global factors F_t and local spatial factor Y^*_{it} link to input and output. To

[2]Here we use the standard notation where a dot in a subscript, means that we averaged over this index.

[3]Pesaran (2006) and Bai (2009) base their asymptotic theory on letting $N, T \to \infty$. Specifically Pesaran (2006) shows that unobserved common factors can be consistently proxied by cross-sectional averages of dependent and independent variables as $N, T \to \infty$, and $T/N \to K$ with $0 \leq K < \infty$. Differently, our approach keeps the length of the panel fixed and only let $N \to \infty$. Because $\mathrm{Cov}(Y_{\cdot t}, \varepsilon_{y,it}) = \sigma_y \mathrm{Cov}(\varepsilon_{\cdot t}, \varepsilon_{y,it}) = \sigma_y \frac{\mathrm{Var}(\varepsilon_{y,it})}{N} \to 0$ as $N \to \infty$, asymptotically $(\varepsilon_x, \varepsilon_y)$ is independent of (Z, F_t) as assumed by our model.

clean from these local and global factors we use Mastromarco et al. (2025), hence we model their link with X and Y through a nonparametric nonseparable model $X = \varphi_x(Z, U_x)$ and $Y = \varphi_y(Z, U_y)$ (Imbens and Newey 2009), where the Z variables are $F_t = (t, \bar{\boldsymbol{x}}_t')'$, as global factor proxies and $Y_{it}^* = \sum_{j=1}^{N} w_{ij} Y_{jt}$ as local spatial proxies. So we use the following model

$$\begin{cases} Y = \varphi_y(Z, U_y) \\ X_j = \varphi_{x_j}(Z, U_x) \quad \text{for } j = 1, \dots, q, \end{cases} \tag{1}$$

where the functions $\varphi_\ell(\cdot, U_\ell)$ are nonseparable and monotone increasing in U_ℓ, $\ell = y, x_1, \dots, x_q$. As explained in details in Mastromarco et al. (2025), the unobserved variables U_ℓ are independent of Z, this assumption is part of the model and it is needed to identify each individual equation in (1).[4] We assume, without loss of generality, that U_ℓ are uniformly distributed on $[0, 1]$. Under these assumptions U_ℓ are identified by the conditional distribution of the input and the outputs given Z:

$$\begin{cases} U_y = F_{Y|Z}(Y|Z) \\ U_{x_j} = F_{X_j|Z}(X_j|Z) \quad \text{for } j = 1, \dots, q, \end{cases} \tag{2}$$

It is useful to notice that $\varphi_y(Z, U_y) = F_{Y|Z}^{-1}(U_y|Z)$, i.e. the conditional quantile of Y given Z evaluated at $U_y \in [0, 1]$. The same is true for $X_1, \dots, X_q$, each function $\varphi_{x_j}(Z, U_{x_j}) = F_{X_j|Z}^{-1}(U_{x_j}|Z)$, $j = 1, \dots, q$ has the same conditional quantile interpretation. The choice of a uniform distribution for U is just a matter of scaling U, so this assumption has no effect on the analysis.

Since the functions φ_ℓ are unknown, the values $U_{\ell,it}$ are not observed but they can be estimated by nonparametric methods by estimating the appropriate conditional distribution functions:

$$\widehat{U}_{y,it} = \widehat{F}_{Y|Z}(Y_{it}|Z_{it}) = \frac{\sum_{s=1}^{T} \sum_{k=1}^{n} G_{h_y}(Y_{ks} - Y_{it}) K_{h_z}(Z_{ks} - Z_{it})}{\sum_{s=1}^{T} \sum_{k=1}^{n} K_{h_z}(Z_{ks} - Z_{it})}, \tag{3}$$

$$\widehat{U}_{x_j,it} = \widehat{F}_{X_j|Z}(X_{j,it}|Z_{it}) = \frac{\sum_{s=1}^{T} \sum_{k=1}^{n} G_{h_{x_j}}(X_{j,ks} - X_{j,it}) K_{h_z}(Z_{ks} - Z_{it})}{\sum_{s=1}^{T} \sum_{k=1}^{n} K_{h_z}(Z_{ks} - Z_{it})}, \tag{4}$$

where now optimal bandwidths h_z, h_y and h_{x_j} can be obtained for each equation, by the LSCV techniques described in Li et al. (2013) and we avoid the problem of selecting optimal

[4]This kind of models (control functions) have been used e.g. in Matzkin (2003), or Imbens and Newey (2009) in a different context where Z play the role of instruments to address endogeneity issues in regression models and in Simar et al. (2016) to identify latent heterogeneity in frontier models.

bandwidths h_z when estimating the boundary of some conditional distribution function and all the issues explained in Mastromarco et al. (2025). Here the kernels used are standard: $K_{h_z}(\cdot)$ are usual kernels for estimating densities and $G_{h_\ell}(\cdot)$ are cumulative kernels used for estimating distribution functions (cdf). For example in the output case $G_{h_y}(Y_{kt} - Y_{it}) = G\big((Y_{kt} - Y_{it})/h_y\big)$ and G is a cdf defined as $G(v) = \int_{-\infty}^{v} w(u)du$ for some kernel density function $w(\cdot)$ (see e.g. Li et al., 2013 for details). Note again that here we are interested in the estimation of the distribution on its full range and not only on the boundary of their support where the data can be rather sparse.

2.1 Estimation of the "pure" efficiencies

In the second stage, we can now estimate the production frontier for these whitened output and inputs and so we obtain for each observation (i, t) a measure of "pure" efficiency. This approach enables us to accommodate both time and spatial dependence and obtain more reliable measure of efficiency. Moreover, as pointed by Mastromarco et al. (2025), by cleaning external factors dependence in the first stage, we avoid the problem of curse of dimensionality due to the dimension of the external variables when estimating the pure order-m production frontier.

In practice this leads to estimate the attainable set of pure inputs and output (U_x, U_y). The latter is defined as

$$\Psi = \left\{(u_x, u_y) \in \mathbb{R}^{p+1} | H_{U_x,U_y}(u_x, u_y) = \text{Prob}(U_x \leq u_x, U_y \geq u_y) > 0\right\}.$$

The nonparametric FDH estimator is obtained by plugging the empirical estimators $\widehat{H}_{U_x,U_y}(u_x, u_y)$ obtained with the observed residuals defined in (3) and (4). As shown in Mastromarco et al. (2025), replacing the unobserved (u_x, u_y) by their empirical counterparts $(\widehat{u}_x, \widehat{u}_y)$ does not change the usual statistical properties of frontier estimators. So we have the consistency for the full-frontier FDH estimator and $\sqrt{n}$-consistency and asymptotic normality for the robust order-m frontiers. The conditional FDH estimator would keep its usual nonparametric rate of convergence i.e. $n^{\frac{1}{p+1}}$.

We can estimate the output frontier and its order-m robust version using standard techniques. For the full frontier, it is defined, at each time period t in pure units as:

$$\phi^t(u_x) = \sup\{u_y \mid S_{U_y|U_x}(u_y \mid u_x) > 0\}, \tag{5}$$

where $S_{U_y|U_x}(u_y \mid u_x) = \mathbb{P}(U_y \geq u_y \mid U_x \leq u_x)$. Thus, $\phi(u_x)$ represents the maximal achievable output level in pure units for units operating at the input level u_x in pure units.

For the order-m frontier, we have, at each time period, for a given m:

$$\begin{aligned}\phi_m^t(u_x) &= \mathbb{E}\left[\sup(u_{y,1,t},\ldots,u_{y,m,t}) \mid U_x \le u_x\right],\\ &= \int_0^1 S^m_{U_y|U_x}(u_y \mid u_x)\, u_y,\end{aligned} \tag{6}$$

which provides, for finite m, a less extreme benchmark than the full frontier $\phi^t(u_x)$. As shown in Cazals et al. (2002), as $m \to \infty$, we have $\phi_m^t(u_x) \to \phi^t(u_x)$.

As proved in Mastromarco et al. (2025), the frontiers in pure units can be transformed back into the original units for both the full and order-m frontiers.

The nonparametric estimator of the frontier in pure units is obtained using the predicted values of inputs and outputs in the space of pure units, $\{(\widehat{u}_{x,it}, \widehat{u}_{y,it})\}_{i=1}^n$ $t = 1,\ldots,T$ by substituting the empirical estimator of $S_{u_y|u_x}(u_y \mid u_x)$ into equations (5) and (6), respectively. The empirical survival function is given by:

$$\widehat{S}_{u_y|u_x}(u_y \mid u_x) = \frac{\sum_{i=1}^n \sum_{t=1}^T \mathbb{1}(\widehat{u}_{x,it} \le u_x, \widehat{u}_{y,it} \ge u_y)}{\sum_{i=1}^n \mathbb{1}(\widehat{u}_{x,it} \le u_x)}. \tag{7}$$

The FDH estimator of the full frontier $\phi(u_{x,it})$ in pure units is:

$$\begin{aligned}\widehat{\phi}(u_x) &= \sup\{u_{y,i} \mid \widehat{S}_{u_y|u_x}(u_y \mid u_x) > 0\},\\ &= \max_{(i,t)|\widehat{u}_{x,it} \le u_x} \widehat{u}_{y,it}.\end{aligned} \tag{8}$$

The order-m frontier in pure units is given by the integral:

$$\widehat{\phi}_m(u_x) = \int_0^1 \widehat{S}^m_{u_y|u_x}(u_y \mid u_x)\, du_y, \tag{9}$$

where an exact formula is provided in Cazals et al. (2002).

Farrell-type efficiency estimate is given by

$$\widehat{\theta}\,(x, y|z, t) = \frac{\widehat{\phi}(u_{x,it})}{u_{y,it}} \ge 1, \tag{10}$$

with equality to 1 for points on the estimated pure efficiency frontier.

Estimates of the frontiers in original units are easy to recover for the full frontier as:

$$\widehat{\tau}(x, z, t) = \widehat{F}^{-1}_{Y|Z,T}(\widehat{\phi}(\hat{u}_{x,it}) \mid z, t), \tag{11}$$

where $\hat{u}_{y,it} = \widehat{F}_{Y|Z}(y|z,t)$ and $\widehat{F}^{-1}_{Y|Z,T}(\cdot|z,t)$ is the nonparametric estimator of the conditional quantile of Y given $Z = z$ at $T = t$ (see Li et al. 2013 for computations and properties).

Finally if Farrell-type efficiency estimate is given by

$$\widehat{\lambda}\left(x, y|z, t\right) = \frac{\widehat{\tau}(x, z, t)}{y} \geq 1, \tag{12}$$

with equality to 1 for points on the estimated conditional frontier.

2.2 Malmquist indices

To analyze productivity changes across European regions over time, we estimate Malmquist indices. These indices measure relative shifts in productivity by comparing distances of observations to the boundary of the production technology. When the technology exhibits variable returns to scale (VRS), Malmquist indices require distances to the boundary of the cone spanned by the production set Ψ. A well-known difficulty, however, is that data are typically not observed in the neighborhood of the conical boundary, except at the points where the hull is tangent to Ψ. This makes direct inference on productivity change particularly challenging.

Recent work by Kneip et al. (2021, 2025) has provided a rigorous foundation to address this issue and to enable more reliable inference on Malmquist indices and their geometric means. In their 2021 paper, Kneip et al. (2021) develop the statistical properties of a DEA-type estimator of the distance from a point to the boundary of the cone spanned by a convex production set. This so-called conical DEA (CDEA) estimator allows for consistent estimation of Malmquist indices under convex technologies. Subsequently, Kneip et al. (2025) extend the analysis to non-convex production sets by introducing Conical Free Disposal Hull (CFDH) estimators, which preserve the same inferential advantages when convexity cannot be assumed.

These methodological advances considerably expand the scope of productivity analysis. In our approach the production set in pure units cannot be assumed to be convex. Hence, in the empirical application that follows, we build on their results by employing CFDH estimators to identify and disentangle the different sources of productivity change across units.

Following the output-oriented decomposition proposed in Simar and Wilson (1998, 2019, 2023), the Malmquist index can be separated into distinct components capturing changes in (i) technical efficiency under VRS or CRS, (ii) technology, (iii) scale efficiency, and (iv) returns to scale of the technology between two periods. This decomposition allows us to identify the sources of productivity change more precisely. In the empirical analysis, we report Malmquist indices and their components, along with confidence intervals constructed using the statistical results of Kneip et al. (2025).

Significant departures from unity at the 10%, 5%, and 1% levels are indicated by one, two, and three asterisks, respectively, based on whether confidence intervals cover one or whether their bounds lie strictly above or below unity.

The operator $C(\cdot)$ defines the cone spanned by the set Ψ^t as:

$$C(\Psi^t) := \left\{(u_x, u_y) \,\middle|\, u_x = a\tilde{u_x}, u_y = a\tilde{u_y} \text{ for some } (\tilde{u_x}, \tilde{u_y}) \in \Psi^t \text{ and any } a \in \mathbb{R}^1_+\right\} \tag{13}$$

The frontier of $C(\Psi^t)$, denoted as $C^\partial(\Psi^t)$, is defined as:

$$C^\partial(\Psi^t) := \left\{(u_x, u_y) \,\middle|\, (u_x, u_y) \in C(\Psi^t) \text{ and } (\theta u_x, \frac{1}{\theta}u_y) \notin C(\Psi^t) \text{ for all } \theta \in (0,1)\right\} \tag{14}$$

For a sample χ_n of "pure" input-output combinations for n units observed in periods $t = 1$ and 2, let $W_i^t := (u_{x,i}^t, u_{y,i}^t)$ for $t \in \{1, 2\}$, so χ_n is represented by $\chi_n = \{W_i^1, W_i^2\}_{i=1}^n$, the hyperbolic Malmquist index M_i is given by:

$$M_i := \left(\frac{\theta(W_i^2 \mid C(\Psi^1))}{\theta(W_i^1 \mid C(\Psi^1))} \times \frac{\theta(W_i^2 \mid C(\Psi^2))}{\theta(W_i^1 \mid C(\Psi^2))}\right)^{1/2} \tag{15}$$

The index quantifies the productivity shift of unit i from period 1 to 2, computed as the geometric mean of two ratios that each quantify a productivity shift. In the first case, productivity is gauged against the frontier of $C(\Psi^1)$, and in the latter, against $C(\Psi^2)$. Thus, $M_i >, =,$ or < 1 indicates whether productivity for unit i has improved, remained constant, or declined from period 1 to 2.

Its interpretation is straightforward:

$$M_i^{1,2} \begin{cases} > 1 & \text{if productivity increases;} \\ = 1 & \text{if productivity remains unchanged;} \\ < 1 & \text{if productivity decreases.} \end{cases}$$

Following Simar and Wilson (1998, 2019, 2023) the Malmquist index can be decomposed into distinct components as:

$$
\begin{aligned}
M_i^{1,2} = &\left(\frac{\theta(X_i^2, Y_i^2 \mid \Psi^2)}{\theta(X_i^1, Y_i^1 \mid \Psi^1)}\right) \times \\
&\left(\frac{\theta(X_i^2, Y_i^2 \mid \Psi^1)}{\theta(X_i^2, Y_i^2 \mid \Psi^2)} \times \frac{\theta(X_i^1, Y_i^1 \mid \Psi^1)}{\theta(X_i^1, Y_i^1 \mid \Psi^2)}\right)^{1/2} \times \\
&\left(\frac{\theta(X_i^2, Y_i^2 \mid C(\Psi^2))/\theta(X_i^2, Y_i^2 \mid \Psi^2)}{\theta(X_i^1, Y_i^1 \mid C(\Psi^1))/\theta(X_i^1, Y_i^1 \mid \Psi^1)}\right)^{1/2} \times \\
&\left(\frac{\theta(X_i^1, Y_i^1 \mid C(\Psi^1))/\theta(X_i^1, Y_i^1 \mid \Psi^1)}{\theta(X_i^1, Y_i^1 \mid C(\Psi^1))/\theta(X_i^1, Y_i^1 \mid \Psi^2)} \times \frac{\theta(X_i^2, Y_i^2 \mid C(\Psi^1))/\theta(X_i^2, Y_i^2 \mid \Psi^1)}{\theta(X_i^2, Y_i^2 \mid C(\Psi^2))/\theta(X_i^2, Y_i^2 \mid \Psi^2)}\right)^{1/2}
\end{aligned}
$$

Here, the first component measures changes in technical efficiency under either VRS or CRS; the second reflects shifts in technology; the third captures changes in scale efficiency; and the fourth measures changes in scale of the technology between periods 1 and 2. Confidence intervals for all components are obtained using the inference framework developed by Kneip et al. (2025).

3 Data

The dataset is collected from "EUROSTAT, Cambridge Econometrics European Regional Database (ERD)," over the period 1980–2022 (42 years) for a total of 202 regions in EU15 (Austria (AT), Belgium (BE), Germany (DE), Denmark (DK), Greece (EL), Spain (ES), Finland (FI), France (FR), Ireland (IE), Italy (IT), Luxembourg (LU), Netherlands (NL), Portugal (PT), Sweden (SE), United Kingdom (UK)).[5]

Regional output is calculated as regional gross value added (GVA) plus taxes less subsidies on products, measured at constant euro price in 2005. Labour is measured as total employment in thousands, and capital (in millions Euros) is constructed using the perpetual inventory method (PIM).[6] All three variables are logged before estimation.

To capture spatial spillovers in production, we calculated the term are given by $y_{it}^* =$

[5]While the original EU15 data covers the period 1980-2022, the data for the 12 new member states EU27 countries (not including Croatia) are only available during 1990-2022. To employ the longer period (1980-2022), we consider the dataset consisting of 202 regions in the EU15.

[6]PIM is necessitated by the lack of the capital stock data in all EU regions. For an individual region, the capital stock is constructed as $K_t = K_{t-1}(1-\theta) + I_t$, where I_t is investment (gross fixed capital formation measured at constant euro price in 2005) and θ is the rate of depreciation assumed to be 6% (*e.g.*, Hall and Jones, 1999; Iyer *et al.*, 2008). Repair and maintenance are assumed to keep the physical production capabilities of an asset constant during its lifetime. Initial capital stocks are constructed, assuming that capital and output grow at the same rate. Specifically, for region with investment data beginning in 1980, we set the initial stock, $K_{1980} = I_{1980}/(g+\theta)$, where g is the 10-year output growth rate from 1980 to 1990. Estimated capital stock includes both residential and non-residential capital.

$\sum_{j=1}^{N} w_{ij} y_{jt}$ with w_{ij} being the (i,j)-th element of the spatial weighting matrix. To capture technological proximity among EU regions we construct the spatial weighting matrix based on technological distance (Basile et al. 2012). We construct the dissimilarity measure by

$$tech_{ij} = \frac{\sum\limits_{k=1}^{K} |s_{ik} - s_{jk}|}{\sum\limits_{k=1}^{K} (s_{ik} + s_{jk})}, \; i, j = 1, ..., N \tag{16}$$

where s_{ik} is the employment share of sector k at region i with $K = 6$.[7] In the literature on the economic structure this measure of dissimilarity has been preferred to the Euclidean distance (e.g. De Benedictis and Tajoli 2007)

We then construct the row-sum normailised weights matrix with inverse technological distance, denoted W_{tech} as a measure of technological proximity. The main idea is that regions similar in technology proximity, will be more receptive to externally produced knowledge. A number of studies suggest that being technologically similar to other regions increases the likelihood to absorb new knowledge produced outside, because the higher is the likelihood that the production knowledge can be understood and efficiently adopted (e.g. Bode 2004, Aldieri and Cincera 2009).

4 Results

Figure 1 shows that the share of observations lying above the order–m frontier declines monotonically as m increases, indicating that extreme points exert limited influence and that our frontier estimates are well behaved. The two panels in Figure 2 confirm that the estimated efficient frontiers based on the full sample, $\widehat{\phi}(\hat{u}_y)$, and on the order–$m$ estimator, $\widehat{\phi}_m(\hat{u}_y)$ (here $m = 500$), are closely aligned, while the "pure" input–output projections exhibit the expected outward shifts over time. The distributions of "pure" inefficiency scores (Figure 3, left panel) are concentrated near zero with a right tail, and the order–m version closely tracks the full-sample counterpart, reinforcing the robustness of our efficiency measures.

Turning to productivity change, the time–series distributions of the yearly geometric means of the Malmquist index (and its components) computed across all EU regions (Figure 4) reveal fluctuations around unity with episodic growth spurts. The year-by-year decomposition (Table 2) shows that technological change is the primary driver of productivity dynamics: it

[7] In the Cambridge Econometrics database, the NACE2 Sectors are aggregated as follows: 1. Agriculture, Forestry and Fishing; 2. Industry - excluding Construction; 3. Construction; 4. Wholesale, Retail, Transport, Accommodation and Food Services, Information and Communication; 5. Financial and Business Services; 6. Non-market Services.

exceeds unity in most years (e.g., 1985–1987, 1997–2000, 2007–2009, 2018–2020), while both efficiency change and scale-efficiency change are frequently below one. For instance, 1985–1986 shows strong technological progress (1.1125***) and scale-of-technology expansion (1.2307***) but large efficiency losses (0.9180***) and scale-efficiency declines (0.7994***). Similarly, in 2007–2008 the Malmquist index is 1.0176***, with technology (1.0435***) and scale of technology (1.0743***) offsetting efficiency deterioration (0.9786***). Notably, during 2019–2020, the Malmquist index rises to 1.1035***, supported by 1.0617** in technology and 1.0695*** in scale of technology. By contrast, downturns such as 2009–2010 (0.9764***) and 2016–2017 (0.9798***) coincide with weak or negative technology and persistent efficiency and scale inefficiencies. Over the long run, the output-direction aggregates indicate an overall gain for 1980–2020 (Malmquist 1.0419**), driven by strong technological progress (1.2040***) and an expansion in the scale of technology (1.4481***), offset by persistent declines in efficiency (0.8688***) and scale efficiency (0.6888***). Extending to 1980–2022, the overall Malmquist drops below unity (0.9616*), with technology still above one (1.1420***) but continued headwinds from efficiency (0.8497***) and scale efficiency (0.6234***).

Before turning to the cross-sectional evidence, note that for each EU region we compute the geometric mean of its yearly Malmquist indices and their components over the full sample period. These region-specific aggregates — reported in Table 1 — form the basis of the distributions displayed in Figure 5. Cross-sectional distributions (Figure 5) and the regional panel in Table 1 document substantial heterogeneity across EU regions. Several regions display pronounced gains (e.g., IDs 55, 58, 59, 138, and 153 with Malmquist $> 1.35^{***}$, and an outlier at ID 197), typically associated with strong technological advances and large scale-of-technology effects. Conversely, a nontrivial group experiences contractions (e.g., IDs 68, 170, 202) where efficiency and scale-efficiency losses dominate. The pattern that emerges is one of broadly positive technological progress coupled with widespread slippage in (scale) efficiency; distinguishing these forces is therefore crucial when interpreting regional convergence and in designing policies aimed at facilitating the absorption of new technologies while mitigating structural inefficiencies.

Overall, the results underline that the main source of productivity growth in EU regions is technological progress, while the contribution of efficiency change remains limited or even negative in certain subperiods. This pattern indicates that regional productivity advances have been largely frontier-driven, reflecting the diffusion of innovation and technological upgrading rather than generalised improvements in managerial or allocative efficiency. The outward shift of the production frontier suggests that new technologies, digital processes, and innovations have expanded potential output, but the heterogeneous ability of regions to internalise these advances has generated persistent efficiency gaps. The evidence therefore points to a frontier-driven rather than catch-up-driven growth process, consistent with a regime in which innovation diffusion outpaces efficiency improvements. Several episodes—most notably 1985–1987, 1997–2000, and 2018–2020—display strong technological progress coinciding with short-term efficiency losses. Such episodes can be interpreted as technological restructuring phases: the introduction of new production techniques, digital technologies, or institutional reforms may temporarily displace existing processes, producing adjustment costs that manifest as efficiency setbacks (Acemoglu et al. 2006, Moretti 2021). Over time, however, the technology component dominates, leading to a higher long-run productivity level. The scale-efficiency term in Table 3 shows moderate yet persistent fluctuations. It tends to rise in expansionary periods, when production scale approaches optimal capacity, and to decline during downturns, when under-utilization of inputs increases. This cyclical behavior indicates that scale effects amplify rather than generate productivity dynamics and that technological progress remains the key structural driver.

Global technological shocks—such as the diffusion of ICT in the late 1990s or the post-crisis digital transformation in the 2010s—appear to dominate local spatial effects in explaining productivity surges and slowdowns. From a policy perspective, these findings suggest that productivity resilience depends less on location within a spatial network and more on the ability to absorb and adapt to global technological shifts. Regions and sectors that combine innovation investments with rapid adaptation of organisational practices are better positioned to transform frontier shifts into sustained efficiency gains. Hence, policy interventions should focus on strengthening absorptive capacity (i.e. human capital), supporting digital and green transitions, and smoothing the adjustment costs that accompany frontier expansions (Lucas 1988, Acemoglu et al. 2006). In doing so, the temporary inefficiency losses observed during innovation waves can be converted into lasting productivity improvements.

This evidence suggests a transition towards a resilience-based growth model, in which productivity advances depend on the capability to sustain efficiency during phases of technological turbulence. Building such resilience—through coordinated innovation policies and investment in absorptive capacity—would help mitigate the transitory inefficiency losses detected in our results and promote more balanced and persistent productivity improvements across European regions (OECD 2021, Commission 2019).

5 Conclusions

This paper has proposed a novel nonparametric panel data framework for measuring productivity and efficiency that explicitly incorporates both global and local spatial dependencies. By combining recent developments in conditional frontier estimation with spatial panel techniques, our approach provides a flexible and fully nonparametric tool to assess the dynamics of productivity across units exposed to heterogeneous external environments and interregional linkages.

The empirical application to EU regions over 1980–2022 yields several important insights. First, productivity growth in Europe has been largely frontier-driven, with technological progress—rather than efficiency improvements—emerging as the main source of gains. This suggests that innovation diffusion and technological upgrading have expanded the production frontier, but regions' ability to internalize these advances remains uneven, generating persistent efficiency gaps. Second, spatial heterogeneity plays a non-negligible role: while some regions experienced substantial productivity gains linked to technological and scale-of-technology effects, others faced stagnation or decline due to efficiency and scale-efficiency losses. These contrasting patterns point to the importance of regional absorptive capacity and the mechanisms governing technology adoption and adaptation.

A further contribution of this study is methodological. We take the "pure" inputs, outputs, and efficiency measures obtained via the indirect, nonseparable control–function approach of Mastromarco et al. (2025), and use them to construct Malmquist indices. Because the production set in pure units need not be convex, we employ recent conical FDH (CFDH) estimators developed for non–convex technologies (Kneip et al. 2025). This combination yields a decomposition of productivity change (technology, efficiency, scale efficiency, and scale of technology) that is valid without convexity or separability assumptions and remains coherent when global and local cross–sectional dependence is removed in the first stage.

From a policy perspective, our findings underscore that productivity resilience depends not only on exposure to global technological shocks but also on the capacity to absorb and transform them into lasting efficiency gains. Strengthening human capital, fostering digital and green transitions, and improving organizational adaptability are therefore key to transforming frontier shifts into sustainable regional growth. In particular, the evidence supports a resilience-based growth model, where long-term performance hinges on maintaining efficiency during phases of technological changes and minimizing the adjustment costs associated with innovations.

Future research could extend this framework to integrate endogenous network structures to capture the evolution of spatial linkages over time.

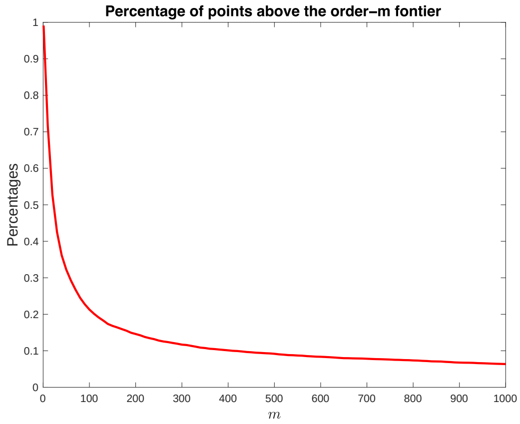

Figure 1: Percentage of points above the order - m frontier at each value of m.

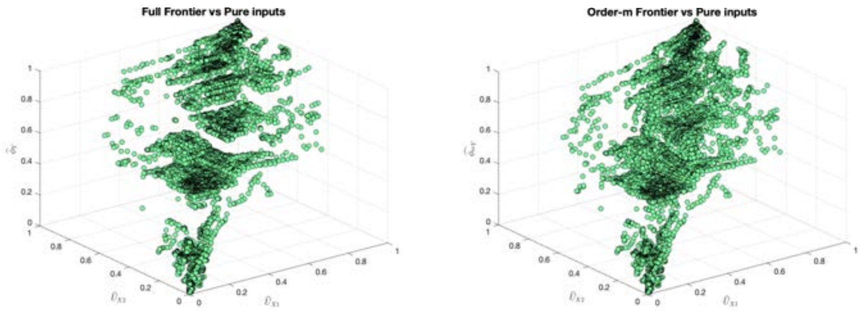

Figure 2: EU regions: Estimated “pure” inputs and outputs and the estimated efficient frontiers $\widehat{\phi}(\hat{u}_y)$ and $\widehat{\phi}_m(\hat{u}_y)$, here $m = 500$.

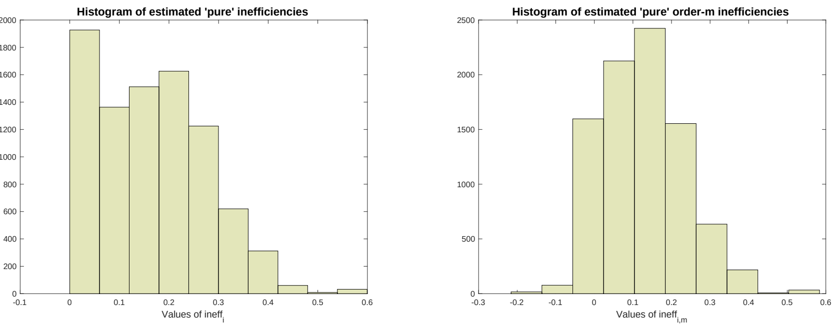

Figure 3: Distribution of the estimated “pure” inefficiencies, relative to the frontier estimates (full and order-m).

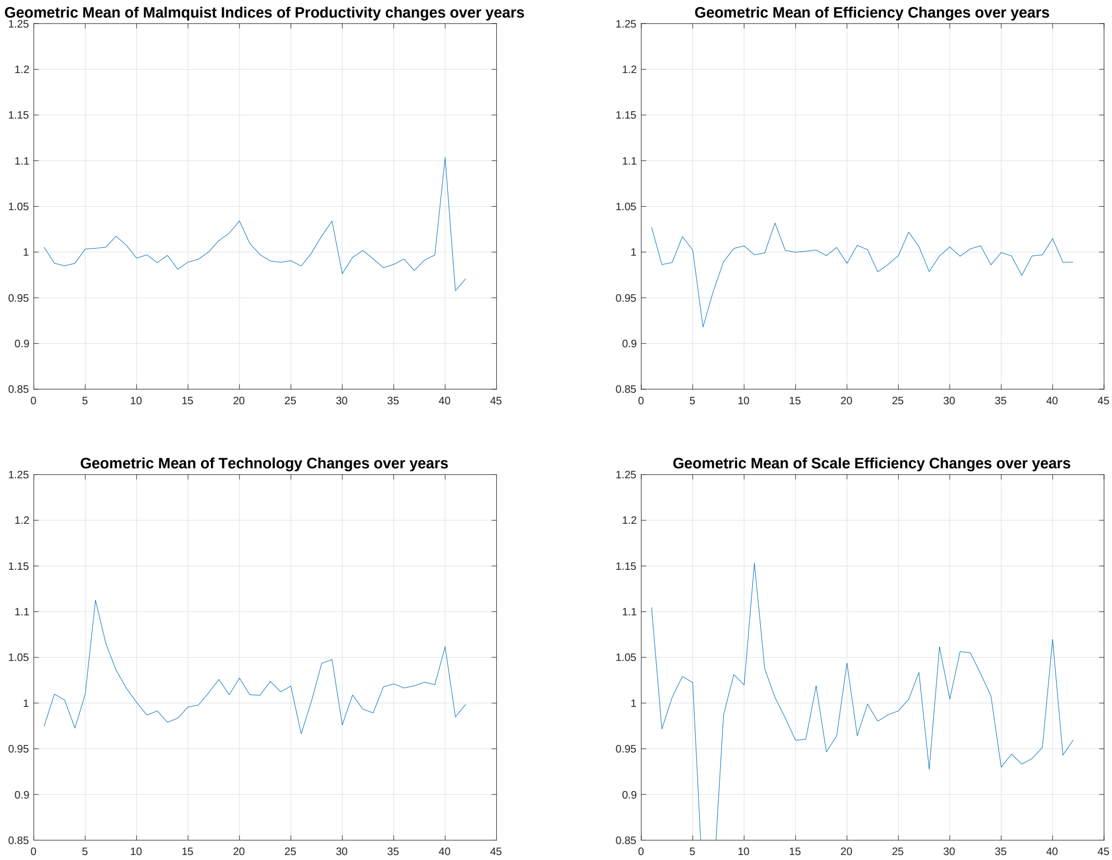

Figure 4: Distribution over time of the geometric mean of estimated of changes in MPI, technical efficiency, technology and scale efficiency

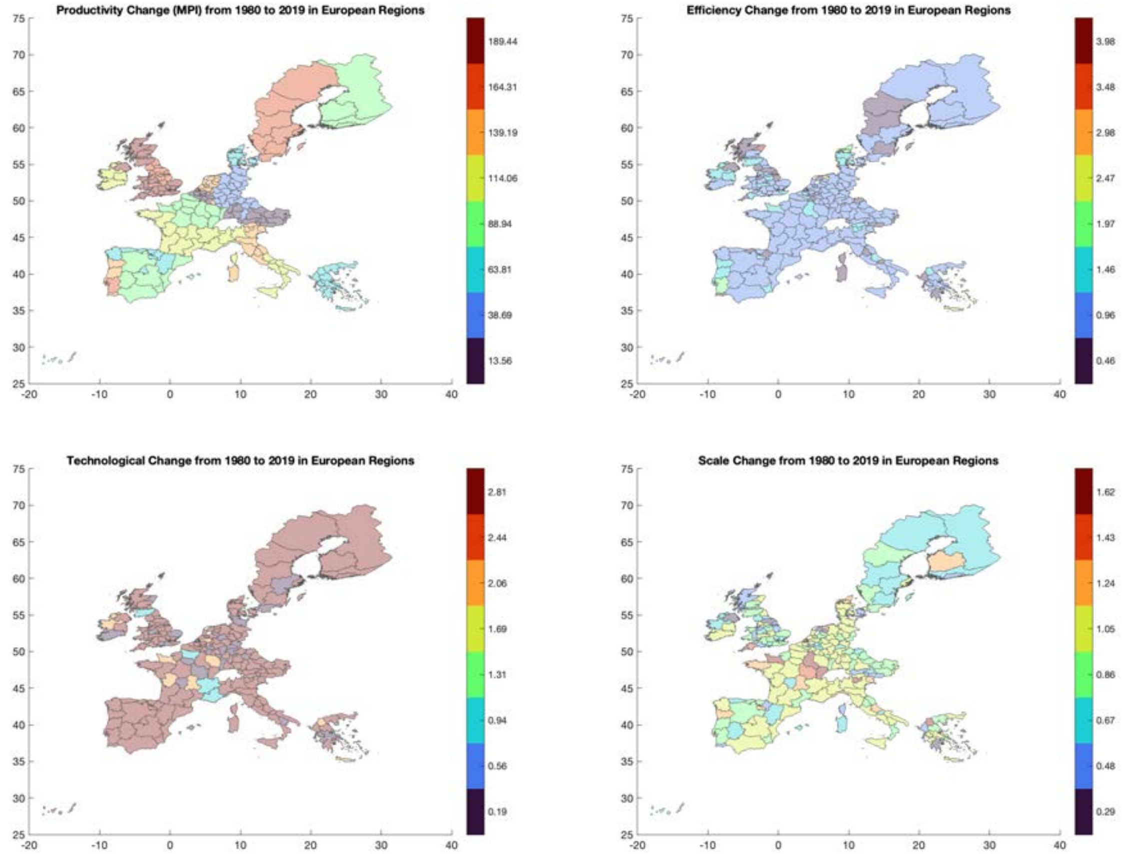

Figure 5: Distribution over EU regions of the geometric mean of estimated of changes in MPI, technical efficiency, technology and scale efficiency

Table 1: Mean Productivity Change and Its Components for EU Regions, 1980-2019, Output Direction.

$Region$	$Malmquist$	$Eff-changes$	$Tech-changes$	$ScaleEff-ch$	$ScaleTech-ch$
1	0.6695***	1		0.3509***	
2	0.8197***	0.7791***	0.9376**	0.5633***	1.9922***
3	0.9768***	1	0.9957	0.652***	1.5046**
4	0.5511***	0.4675***	0.9604	0.8223	1.4927
5	0.7897***	0.941	0.855***	0.5945***	1.6512**
6	0.91***	0.9033*	1.0093	0.6534***	1.5275**
7	0.7295***	0.598***	0.9004	0.9128	1.4845**
8	0.7729***	0.3975***	1.6105**	1.5344**	0.787
9	0.3541***	1	0.4088***	0.3195***	2.711***
10	1.0668	1	0.9798	0.9597	1.1346
11	1.1568***	1	1.0638	0.8465*	1.2847*
12	0.6199***	0.7038***	1.3495***	0.6405***	1.019
13	1.0157***	1.0158	0.9555	0.6581***	1.59***
14	0.8636***	0.7321*	1.153	0.9925	1.0309
15	1.0411***	1.1431	0.7439***	0.9297	1.3168*
16	0.9381	0.979	0.8864	0.6436***	1.6797***
17	1.2835***	0.7758***	1.6405***	0.8587*	1.1744*
18	0.9263	0.6264***	1.8971***	1.0204	0.7639
19	0.8729	1.1461	1.3411	0.5783**	0.9821
20	0.623***	1	0.9012	0.336***	2.0575*
21	1.0361***	1	1.006	0.5365***	1.9197***
22	1.0432***	1.0859**	0.9166***	0.4975***	2.1066***
23	1.0956***	1.0308	1.0473	0.5464***	1.8574***
24	1.08***	1.0422	1.0334	0.5484***	1.8286***
25	0.9933***	0.9753**	1.0062	0.5368***	1.8858***
26	0.7772***	0.7822***	0.9059	0.577***	1.9009***
27	0.8287***	0.7843**	0.8994	0.7103***	1.654***
28	0.6599***	0.7096***	1.043	0.4827***	1.8472***
29	0.9994	0.8276***	1.1257***	0.6801***	1.5772***
30	0.7556***	0.7803***	0.9638	0.5463***	1.8392***
31	0.9539***	0.8541***	1.0856**	0.5908***	1.7413***
32	0.874	0.8148	1.8971	0.7813	0.7237***
33	1.0586***	1	0.9744	0.639***	1.7001***
34	1.0154***	1.0071	0.9909	0.5288***	1.924***
35	0.8548	0.6063***	1.7403***	0.9789	0.8276
36	0.9186	1.0838**	0.839***	0.5075***	1.9906***
37	0.8827***	0.8185***	1.0441	0.6544***	1.5781**
38	0.9332***	1.0046	1.063**	0.4776***	1.8301***
39	1.0416***	1.0423	0.9947	0.5238***	1.9182***
40	0.9463***	1.0486	0.9633	0.489***	1.9159***
41	0.9751***	1	1.0073	0.506***	1.913***
42	1.035***	1.0272	0.9953	0.5199***	1.9472***
43	1.0427***	1.1241***	0.9471	0.4792***	2.0436***
44	1.0661***	0.9353*	1.1429***	0.5859***	1.7021***
45	0.9228***	1.0824***	0.9388***	0.4507***	2.0152***
46	0.9482	0.9736	1.0616	0.5711***	1.6065***
47	0.9379***	1	1.5149	0.5335***	1.1605
48	1.1315***	1.1181***	1.0348	0.5202***	1.8798***
49	0.9338	0.8952	1.0693	0.7432**	1.3126***
50	1.0191	1.147***	0.9166***	0.4568***	2.1224***

Mean Productivity Change and Its Components for EU Regions, 1980-2019, Output Direction (continued).

51	0.9973	1	1.038	0.673***	1.4275*
52	0.8756***	0.5652***	1.5416***	0.8042***	1.2497***
53	1.2185***	0.9991	1.0216	0.7582*	1.5746***
54	1.526***	1	1.1418*	0.8753	1.527***
55	2.0017***	1.2659	1.5192***	0.964	1.0797
56	0.7695***	0.9068	1.0415	0.4607***	1.7685***
57	1.7171***	1.5241	1.9751	0.6232	0.9153
58	2.3215***	1.4057	1.2326	0.8572	1.563***
59	2.5114***	1	2.145***	1.0726	1.0916
60	0.8969***	1.0727	1.3452***	0.4943***	1.2574**
61	0.8438***	0.7671***	1.1733***	0.6591***	1.4226**
62	1.473**	1.7191	1.3092	0.6109***	1.0713
63	0.5824***	0.455***	1.6405***	0.6689***	1.1663**
64	0.7386***	0.7974***	1.051	0.5912***	1.4907**
65	0.5631***	0.66**	0.9359	0.6201***	1.4704*
66	1.09***	1	1.179	0.605***	1.5283***
67	1.0572	1	0.9502	0.7799	1.4266***
68	0.2064***	0.2573***	0.8887	0.6905***	1.3072**
69	1.0259***	1.0765*	0.9327**	0.4947***	2.0655***
70	0.7565***	0.6142***	1.2494	0.6442***	1.5302***
71	0.5685***	0.781	1.4589	0.3599***	1.3865
72	1.2051***	0.8264***	1.2394***	0.7643***	1.5394***
73	0.5554***	0.5569***	1.1634	0.5227***	1.64**
74	1.5559***	1.2498	1.4746	0.6783	1.2447
75	1.1275***	0.7073***	1.2846**	0.8274	1.4997***
76	1.0673***	1	0.9727**	0.5517***	1.9888***
77	1.1719***	0.8704***	1.2394***	0.6988***	1.5544***
78	1.0927***	1.0524	1.0622	0.5442***	1.7963***
79	0.7635***	0.6832***	0.9838	0.5801***	1.9582***
80	1.0488***	1.0073	0.9908	0.5352***	1.9635***
81	1.2091***	1.1136	0.9969	0.5636***	1.9325***
82	0.9896	0.6287***	1.2326	0.825	1.5479***
83	1.0366***	1.0085	0.9585***	0.5335***	2.01***
84	1.2796***	0.9444	1.3489	0.7496	1.3401***
85	0.8885***	0.6416***	1.2065**	0.7258***	1.5814***
86	1.1664***	1.2279	0.8745***	0.7545**	1.4398**
87	1.1309***	0.5349***	1.4123***	1.3167***	1.1369
88	0.7294***	0.5919***	1.0211	0.7211***	1.6736***
89	0.7674***	0.6298***	1.0216	0.7468**	1.597***
90	0.4306***	1	0.9206	0.3156***	1.482
91	1.0001	1	1.0012	0.5161***	1.9356***
92	1.0576***	1.0106	1.0274	0.5427***	1.8768***
93	1.1498	1.3477***	0.906**	0.5933***	1.5873***
94	1.2043***	1.5997**	0.839	0.5329***	1.684***
95	1.3748**	1.6633***	0.7975***	0.5976***	1.7342***
96	0.9488***	0.885***	1.1048***	0.6286***	1.5438**
97	0.9762***	1.0431	0.9458***	0.4945***	2.0011***
98	1.0688	1.1055	1.043	0.5479***	1.6916***
99	0.9869	0.8674***	1.1429**	0.6195***	1.607***
100	1.2776***	1.6705*	0.8202*	0.6424***	1.4516***
101	1.0446***	1.0357	1.0778*	0.5303***	1.7646***

Mean Productivity Change and Its Components for EU Regions, 1980-2019, Output Direction (continued).

102	1.0392***	1.0437	0.927***	0.5188***	2.0704***
103	1.1291***	1.178***	0.9327***	0.4927***	2.0857***
104	1.0658***	1.1152***	0.9307***	0.4913***	2.0901***
105	1.0887	0.711***	1.4848	1.075	0.9593
106	1.1565**	1.1427*	0.9705	0.6548***	1.5926***
107	1.1094***	0.7923***	1.1902***	0.7198***	1.6345***
108	1.0354***	1.0338	0.9966	0.5148***	1.952***
109	1.1427**	1.263***	0.9276	0.5917***	1.6483***
110	1.0193***	1.0003	0.9875	0.555***	1.8591***
111	1.009***	1.0213	0.9782	0.5309***	1.9023***
112	0.3774***	0.5441***	1.2327	0.5128***	1.0974
113	1.2777***	0.6244***	1.2253	1.3707	1.2185***
114	1.0141	1	0.948	0.7212***	1.4834**
115	1.5655***	1	1.137***	0.8548	1.6108***
116	1.0567***	1.0799***	0.9776	0.5126***	1.9525***
117	0.7437***	1		0.5809***	
118	0.9787	1.1712*	1.0362	0.5624***	1.4339**
119	0.9971***	1	0.9985	0.5159***	1.9357***
120	1.5751***	1.2158	1.0143	0.7149***	1.7865***
121	0.6505***	0.6456***	1.0085	0.8969	1.1139
122	0.9495***	1.0821***	0.9527***	0.4635***	1.9872***
123	0.9562***	1.0529***	0.9351***	0.4813***	2.0179***
124	1.04***	1.0573	0.8994**	0.6665***	1.641***
125	0.821***	0.7695***	1.1429***	0.608***	1.5354**
126	0.9285***	1.0349	0.9683**	0.4828***	1.9189***
127	0.6726***	0.748***	1.0954	0.6335***	1.296*
128	1.5401***	1	1.8037**	0.9505	0.8984
129	1.4807***	1.548	1.2063	0.7936	0.9992
130	1.0922***	1.0408	0.9774	0.5395***	1.9902***
131	1.1802***	1.3119***	1.0143	0.4984***	1.7796***
132	0.9777***	0.9951	0.9953	0.5165***	1.9116***
133	0.9449***	1.0289	0.9585**	0.4984***	1.9225***
134	0.5513***	0.7784	1.188	0.5307***	1.1235
135	0.8033***	0.9296	1.0954	0.5956***	1.3246**
136	1.0274***	1	1.0014	0.5282***	1.9426***
137	1.0178***	1	0.8359	1	1.2175***
138	2.5833***	1.1576	2.0874***	1.1471	0.932
139	0.6172***	0.3008***	1.4899	1.103	1.2483*
140	0.7821***	0.3777***	1.1886	1.527	1.1409
141	1.0157	0.8441*	0.9461	0.6856***	1.8551***
142	0.9936***	0.7898***	1.1429***	0.6467***	1.7021***
143	1.1201***	0.9667	0.9738	0.7347***	1.6194***
144	1.0323***	0.9988	0.9828	0.5449***	1.9299***
145	1.0394***	1.0206	0.9891	0.5318***	1.9359***
146	0.8088	1.2371	0.6315***	0.4744***	2.1825**
147	1.0771***	1.0699	0.9946	0.5354***	1.8907***
148	0.776***	0.8264**	0.9059	0.5132***	2.0196***
149	1.549***	1.1852**	1.0434	0.685***	1.8285***
150	0.7056***	0.4988***	1.6857*	0.7385	1.1363
151	1.4887***	0.8829***	1.1391***	0.8752	1.6913***
152	1.7075***	0.9686*	1.4764***	0.8715	1.3701***

Mean Productivity Change and Its Components for EU Regions, 1980-2019, Output Direction (continued).

153	1.8627***	0.8711	1.3931*	1.1461	1.3392***
154	1.0749***	1	1.0849***	0.7178***	1.3803**
155	0.9223	0.7108***	1.1657***	0.7451**	1.494**
156	0.5345***	0.6475***	1.1373	0.6298***	1.1525
157	1.0158	0.7709***	1.0791	0.7575*	1.6121***
158	1.1085***	0.7869***	1.1224***	0.7957	1.5773***
159	0.6862***	0.5809***	1.227	0.6656***	1.4465***
160	0.6936***	0.8711	0.9035	0.6417***	1.3734*
161	0.8003***	0.6192***	1.3397**	0.8928	1.0806
162	0.7708***	0.6731***	1.1013	0.6583***	1.5794***
163	0.8903***	0.9694	0.9642	0.4964***	1.9189***
164	0.6667***	0.6641***	1.0568	0.6691***	1.4198***
165	0.8462***	0.9972	0.9327	0.4405***	2.0655***
166	0.9373***	1	1.1667	0.4913***	1.6353***
167	0.3736***	0.4181***	1.2415	0.3613***	1.9921***
168	0.5214***	0.408***	1.2091	0.6328***	1.6703***
169	0.5608***	0.5319***	1.1585	0.6292***	1.4465***
170	0.5066***	0.2667***	1.8971***	0.986	1.0154
171	1.0802***	0.6837***	1.4726***	0.828*	1.2956***
172	0.8739***	0.8018***	1.1612*	0.5713***	1.6431***
173	1.2435***	0.7772***	1.2394***	0.8312	1.5531***
174	1.1878***	0.9957	1.0541	0.6192***	1.8276***
175	0.4681***	0.4476***	1.2328**	0.6339***	1.3382
176	1.6492***	1.0555	1.2416	0.7943	1.5844***
177	0.9222	0.664***	1.125	0.7279***	1.696***
178	0.8831***	1.0126	0.9471	0.4527***	2.0341***
179	0.9967	0.9032*	1.0516	0.5935***	1.768***
180	0.8764***	0.7327***	1.065	0.6281***	1.7883***
181	0.7196***	0.601***	1.2394**	0.6275***	1.5394**
182	1.0328***	1	1.0108	0.7952	1.2849
183	0.9053***	0.9701	0.9727	0.5369***	1.7871***
184	0.8776***	1	1.0591	0.46***	1.8014***
185	0.8735***	1	0.9618	0.4588***	1.9794***
186	1.058***	0.722***	1.0763	0.7976	1.707***
187	0.7965***	0.7798***	0.9917	0.5693***	1.8091***
188	0.9617	0.9066*	0.9382	0.5506***	2.0535***
189	0.9456	0.7513***	1.1549***	0.6725***	1.6205***
190	1.3427***	0.8067***	1.4156***	0.8724	1.3478**
191	1.0166***	0.9317	0.9966	0.568***	1.9275***
192	0.7996***	0.4854***	1.4459***	0.8634	1.3195***
193	0.4619***	0.2543***	1.6425	0.9641	1.1474
194	1.4605***	1.3421	1.2271	0.5956***	1.489***
195	1.1728***	0.8705**	1.1395	0.7062***	1.6744***
196	0.8615***	0.472***	1.5025***	0.9567	1.2699***
197	4.2358	1	3.7568***	1.7536***	0.643
198	0.5463***	0.3948***	1.4405	0.9954	0.9651
199	0.8564***	0.8077***	1.0856	0.545***	1.792***
200	0.714***	0.6817***	1.0616	0.5493***	1.7961***
201	1.2318***	0.8402	1.8971***	0.7828**	0.9872
202	0.2049***	0.1954***	1.043*	0.6142***	1.637**

Table 2: Mean Productivity Change and Its Components for EU Regions, 1980-2019, Output Direction.

$Years$	$Malmquist$	$Eff-changes$	$Tech-changes$	$ScaleEff-ch$	$ScaleTech-ch$
1980-1981	1.0054**	1.0272***	0.9746***	1.1047***	0.9076***
1981-1982	0.9878*	0.9863*	1.0098*	0.9717**	1.0207*
1982-1983	0.9850*	0.9886***	1.0033*	1.0062*	0.9869*
1983-1984	0.9877*	1.0169***	0.9727***	1.0292***	0.9702*
1984-1985	1.0033***	1.0023*	1.0098***	1.0225***	0.9696***
1985-1986	1.0042*	0.9180***	1.1125***	0.7994***	1.2307***
1986-1987	1.0054*	0.9572***	1.0654***	0.8007***	1.2335***
1987-1988	1.0173*	0.9894**	1.0362***	0.9873***	1.0054***
1988-1989	1.0075*	1.0040*	1.0163*	1.0312***	0.9577***
1989-1990	0.9934***	1.0068*	1.0007*	1.0199*	0.9670*
1990-1991	0.9970*	0.9970*	0.9870*	1.1531***	0.8787***
1991-1992	0.9884***	0.9991*	0.9914*	1.0377***	0.9617***
1992-1993	0.9964*	1.0317***	0.9790*	1.0061*	0.9805**
1993-1994	0.9812***	1.0019*	0.9835***	0.9837**	1.0123**
1994-1995	0.9891*	0.9999*	0.9958***	0.9594***	1.0355***
1995-1996	0.9921**	1.0009*	0.9978*	0.9604***	1.0344***
1996-1997	1.0002*	1.0023*	1.0112*	1.0188***	0.9686***
1997-1998	1.0125*	0.9961*	1.0259*	0.9466***	1.0471**
1998-1999	1.0208***	1.0051**	1.0091*	0.9642***	1.0441***
1999-2000	1.0341***	0.9876**	1.0273*	1.0438***	0.9764***
2000-2001	1.0095*	1.0074*	1.0092*	0.9643***	1.0297***
2001-2002	0.9972*	1.0026**	1.0085**	0.9988*	0.9874***
2002-2003	0.9902***	0.9784***	1.0238***	0.9802*	1.0085***
2003-2004	0.9888*	0.9865***	1.0123*	0.9871***	1.0030***
2004-2005	0.9906***	0.9962*	1.0186**	0.9915*	0.9847*
2005-2006	0.9847***	1.0219***	0.9664***	1.0041***	0.9930***
2006-2007	0.9989*	1.0060*	1.0019***	1.0336*	0.9588***
2007-2008	1.0176***	0.9786***	1.0435***	0.9276***	1.0743***
2008-2009	1.0339*	0.9958*	1.0476***	1.0614***	0.9336***
2009-2010	0.9764***	1.0056*	0.9762**	1.0043*	0.9905*
2010-2011	0.9942*	0.9955*	1.0089*	1.0563***	0.9371***
2011-2012	1.0017*	1.0036*	0.9934**	1.0550***	0.9524***
2012-2013	0.9926***	1.0069*	0.9892*	1.0321***	0.9656***
2013-2014	0.9830***	0.9861*	1.0177*	1.0080*	0.9718***
2014-2015	0.9865***	0.9995*	1.0210*	0.9299***	1.0395***
2015-2016	0.9924*	0.9958*	1.0165*	0.9442***	1.0384***
2016-2017	0.9798***	0.9744***	1.0189*	0.9333***	1.0574***
2017-2018	0.9913*	0.9958*	1.0228**	0.9393***	1.0363***
2018-2019	0.9967*	0.9969*	1.0202*	0.9515***	1.0300***
2019-2020	1.1035***	1.0147*	1.0617**	1.0695***	0.9577***
2020-2021	0.9577***	0.9888***	0.9849*	0.9431***	1.0423***
2021-2022	0.9708***	0.9890**	0.9987***	0.9597***	1.0239***
1980-2020	1.0419**	0.8688***	1.2040***	0.6888***	1.4481***
1980-2022	0.9616*	0.8497***	1.1420***	0.6234***	1.5919***

6 Appendix

Table 3: Names and codes of the 202 NUTS2 regions

Codes	Names	Codes	Names
AT11	Burgenland	DK01	Hovedstaden
AT12	Niederösterreich	DK02	Sjælland
AT13	Wien	DK03	Syddanmark
AT21	Kärnten	DK04	Midtjylland
AT22	Steiermark	DK05	Nordjylland
AT31	Oberösterreich	EL30	Attiki
AT32	Salzburg	EL41	Voreio Aigaio
AT33	Tirol	EL42	Notio Aigaio
AT34	Vorarlberg	EL43	Kriti
BE10	Région de Bruxelles-Capitale	EL51	Anatoliki Makedonia, Thraki
BE21	Prov. Antwerpen	EL52	Kentriki Makedonia
BE22	Prov. Limburg	EL53	Dytiki Makedonia
BE23	Prov. Oost-Vlaanderen	EL54	Ipeiros
BE24	Prov. Vlaams-Brabant	EL61	Thessalia
BE25	Prov. West-Vlaanderen	EL62	Ionia Nisia
BE31	Prov. Brabant wallon	EL63	Dytiki Ellada
BE32	Prov. Hainaut	EL64	Sterea Ellada
BE33	Prov. Liège	EL65	Peloponnisos
BE34	Prov. Luxembourg	ES11	Galicia
BE35	Prov. Namur	ES12	Principado de Asturias
DE11	Stuttgart	ES13	Cantabria
DE12	Karlsruhe	ES21	País Vasco
DE13	Freiburg	ES22	Comunidad Foral de Navarra
DE14	Tübingen	ES23	La Rioja
DE21	Oberbayern	ES24	Aragón
DE22	Niederbayern	ES30	Comunidad de Madrid
DE23	Oberpfalz	ES41	Castilla y León
DE24	Oberfranken	ES42	Castilla-la Mancha
DE25	Mittelfranken	ES43	Extremadura
DE26	Unterfranken	ES51	Cataluña
DE27	Schwaben	ES52	Comunidad Valenciana
DE50	Bremen	ES53	Illes Balears
DE60	Hamburg	ES61	Andalucía
DE71	Darmstadt	ES62	Región de Murcia
DE72	Gießen	ES70	Canarias
DE73	Kassel	FI19	Länsi-Suomi
DE91	Braunschweig	FI1B	Helsinki-Uusimaa
DE92	Hannover	FI1C	Etelä-Suomi
DE93	Lüneburg	FI1D	Pohjois- ja Itä-Suomi
DE94	Weser-Ems	FI20	Åland
DEA1	Düsseldorf	FR10	Île de France
DEA2	Köln	FRB0	Centre - Val de Loire
DEA3	Münster	FRC1	Bourgogne
DEA4	Detmold	FRC2	Franche-Comté
DEA5	Arnsberg	FRD1	Basse-Normandie
DEB1	Koblenz	FRD2	Haute-Normandie
DEB2	Trier	FRE1	Nord-Pas-de-Calais
DEB3	Rheinhessen-Pfalz	FRE2	Picardie
DEC0	Saarland	FRF1	Alsace
DEF0	Schleswig-Holstein	FRF2	Champagne-Ardenne

References

Acemoglu, D., Aghion, P. and Zilibotti, F.: 2006, Distance to frontier, selection and economic growth, *Journal of European Economic Association* **4**, 37–74.

Aldieri, L. and Cincera, M.: 2009, Geographic and technological R&D spillovers within the triad: micro evidence from US patents, *The Journal of Technology Transfer* **34**(2), 196–211.

Bai, J.: 2009, Panel data models with interactive fixed effects, *Econometrica* **77**, 1229–1279.

Bai, J. and Li, K.: 2021, Dynamic spatial panel data models with common shocks, *Journal of Econometrics* **224**(1), 134–160. Annals Issue: PI Day.

Bai, J. and Ng, S.: 2006, Evaluating latent and observed factors in macroeconomics and finance, *Journal of Econometrics* **131**, 507–537.

Basile, R., Capello, R. and Caragliu, A.: 2012, Technological interdependence and regional growth in europe: proximity and synergy in knowledge spillovers, *Papers in Regional Science* **91**, 697–722.

Bode, E.: 2004, The spatial pattern of localized r&d spillovers: An empirical investigation for germany, *Journal of Economic Geography* **4**, 43–64.

Bădin, L., Daraio, C. and Simar, L.: 2019, A bootstrap based approach for bandwidth selection in estimating conditional efficiency measures, *European Journal of Operational Research* **277**, 784–797.

Caves, D. W., Christensen, L. R. and Diewert, W.: 1982, The economic theory of index numbers and the measurement of input, output, and productivity, *Econometrica* **50**, 1393–1414.

Chen, J., Shin, Y. and Zheng, C.: 2022, Estimation and inference in heterogeneous spatial panels with a multifactor error structure, *Journal of Econometrics* **229**(1), 55–79.

Commission, E.: 2019, Seventh report on economic, social and territorial cohesion, *Technical report*, Directorate-General for Regional and Urban Policy, European Commission, Brussels.

De Benedictis, L. and Tajoli, L.: 2007, Economic integration and similarity in trade structures., *Empirica* **34**, 117–137.

Druska, V. and Horrace, W. C.: 2004, Generalized moments estimation for spatial panel data: Indonesian rice farming, *American Journal of Agricultural Economics* **86**(1), 185–198.

Färe, R., Grosskopf, S., Norris, M. and Zhang, Z.: 1994, Productivity growth, technical progress, and efficiency change in industrialized countries, *American Economic Review* **84**, 66–83.

Florens, J., Simar, L. and van Keilegom, I.: 2014, Frontier estimation in nonparametric location-scale models, *Journal of Econometrics* **178**, 456–470.

Gamerman, D. and Moreira, A. R.: 2004, Multivariate spatial regression models, *Journal of Multivariate Analysis* **91**(2), 262–281.

Glass, A. J., Kenjegalievaa, K. and Sickles, R. C.: 2016, A spatial autoregressive stochastic frontier model for panel data with asymmetric efficiency spillovers, *Journal of Econometrics* **190**, 289–300.

Gude, A., Álvarez, I. and Orea, L.: 2018, Heterogeneous spillovers among Spanish provinces: a generalized spatial stochastic frontier model, *Journal of Productivity Analysis* **50**(3), 155–173.

Imbens, G. W. and Newey, W. K.: 2009, Identification and estimation of triangular simultaneous equations models without additivity, *Econometrica* **77**, 1481–1512.

Kapetanios, G., Pesaran, M. and Yamagata, T.: 2011, Panels with non-stationary multifactor error structures, *Journal of Econometrics* **160**, 326–348.

Kneip, A., Simar, L. and Wilson, P. W.: 2021, Inference in dynamic, nonparametric models of production: Central limit theorems for malmquist indices, *Econometric Theory* **37**, 537–572.

Kneip, A., Simar, L. and Wilson, P. W.: 2025, Conical FDH estimators for testing returns to scale and making inference about changes in productivity, *Econometric Review* **forthcoming**.

Kuersteiner, G. M. and Prucha, I. R.: 2020, Dynamic spatial panel models: Networks, common shocks, and sequential exogeneity, *Econometrica* **88**(5), 2109–2146.

Lu, L.: 2022, Simultaneous spatial panel data models with common shocks, *Journal of Business & Economic Statistics* **0**(0), 1–16.

Lucas, R. E.: 1988, On the mechanics of economic development, *Journal of Monetary Economics* **22**, 3–42.

Mastromarco, C., Serlenga, L. and Shin, Y.: 2013, Globalisation and technological convergence in the EU, *Journal of Productivity Analysis* **40**, 15 – 29.

Mastromarco, C., Serlenga, L. and Shin, Y.: 2016a, Modelling technical efficiency in cross sectionally dependent stochastic frontier panels, *Journal of Applied Econometrics* **31**, 281–297.

Mastromarco, C., Serlenga, L. and Shin, Y.: 2016b, Modelling technical efficiency in cross sectionally dependent stochastic frontier panels, *Journal of Applied Econometrics* **31**(1), 281–297.

Mastromarco, C. and Simar, L.: 2018, Globalization and productivity: A robust nonparametric world frontier analysis, *Economic Modelling* **69**, 134–149.

Mastromarco, C., Simar, L. and van Keilegom, I.: 2025, Estimating nonparametric conditional frontiers and efficiencies: A new approach, *The Econometrics Journal* **28**, 502–528.

Matzkin, R.: 2003, Nonparametric estimation of nonadditive random functions, *Econometrica* **71**, 1339–1375.

Moretti, E.: 2021, The effect of high-tech clusters on the productivity of top inventors, *American Economic Review* **111**(10), 3328–3375.
URL: *https://doi.org/10.1257/aer.20191589*

OECD: 2021, Oecd regional outlook 2021: Addressing covid-19 and moving to net zero carbon, *Technical report*, Organisation for Economic Co-operation and Development, Paris.
URL: *https://doi.org/10.1787/17017efe-en*

Pesaran, M. H.: 2006, Estimation and inference in large heterogeneous panels with a multifactor error structure, *Econometrica* **74 (4)**, 967–1012.

Schmidt, A. M., Moreira, A. R. B., Helfand, S. M. and Fonseca, T. C. O.: 2009, Spatial stochastic frontier models: accounting for unobserved local determinants of inefficiency, *Journal of Productivity Analysis* **31**(2), 101–112.

Schmidt, P. and Sickles, R.: 1984, Production frontiers and panel data, *Journal of Business and Economics Statistics* **2**, 367–374.

Shi, W. and Lee, L.-f.: 2017, Spatial dynamic panel data models with interactive fixed effects, *Journal of Econometrics* **197**(2), 323–347.

Simar, L., Vanhems, A. and van Keilegom, I.: 2016, Unobserved heterogeneity and endogeneity in nonparametric frontier estimation, *Journal of Econometrics* **190**, 360–373.

Simar, L. and Wilson, P. W.: 1998, Sensitivity analysis of efficiency scores: How to bootstrap in nonparametric frontier models, *Management Science* **44**, 49–61.

Simar, L. and Wilson, P. W.: 2019, Central limit theorems and inference for sources of productivity change measured by nonparametric malmquist indices, *European Journal of Operational Research* **277**, 756–769.

Simar, L. and Wilson, P. W.: 2023, Another look at productivity growth in industrialized countries, *Journal of Productivity Analysis* **60**, 257–272.

Yang, C. F.: 2021, Common factors and spatial dependence: an application to us house prices, *Econometric Reviews* **40**(1), 14–50.