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Modeling Regional Productive Performance Using a Spatial Stochastic Frontier Approach: New Evidence for Europe (1995-2007)

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Abstract:

The literature on the measurement of regional convergence at different spatial scales and over different time periods is extensive. This study explores the potential role of variations in European regional technical efficiency as a contributing factor in providing explanation for convergence or divergence. To control for spatial dependence among regions, the paper uses a spatial stochastic frontier approach that integrates spatial econometric techniques with stochastic frontier models, also allowing for non-linear technical progress jointly with time and cross-sectional varying technical efficiency. From the estimated production function, we obtain estimates of the technical efficiency of the investigated 120 NUTS-2 regions of the European Union over the period 1995-2007. Our findings show that geographical externalities affect the EU frontier level, and that European regions have been converging to the frontier at a rate of about 0.8% per year. However, the analyses of the efficiency scores reveal that there is a strong geographic pattern of regional efficiency while the degree of average regional efficiency has increased steadily year by year. Overall, it appears that European regions have converged during the 1995-2007 period in terms of their ability to utilize physical capital and labor to produce gross value added.

Keywords:

Technical efficiency; spillover effects; frontier analysis; stochastic production function; spatial panel model; European regions.

1. Introduction

Since Baumol's (1986) pioneering work, a great number of empirical studies have attempted to test the hypothesis of regional convergence, according to which poor regions tends to grow faster than rich regions, such that there exists a process of catching-up of less developed regions with the richer regions in terms of the level of per capita income (Barro and Sala-i-Martin, 1991).

Following this literature, the primary sources of regional economic growth and development are centered on two basic explanations, factor accumulation and productivity growth, total factor productivity (TFP) being considered as the most important driver behind economic growth (e.g. Caselli, 2005; Parente and Prescott, 2005).

Therefore, proper understanding about how the productivity of regions evolves over time is essential to an understanding of the current and future trends in regional income levels, and growth in per capita income. In this sense, as TFP growth is often decomposed (ignoring the scale component) into technical change (technological innovation) and technical efficiency (technological catch-up), efficiency is an important component of productivity (Färe *et al.*, 1994; Kumar and Russell, 2002). Then, the exploration of variations in regional efficiency can provide new insights in the explanation for convergence or divergence of regions (see Crespo-Cuaresma *et al.*, 2014, and Piribauer, 2016, for recent empirical studies that analyze regional growth determinants and income convergence in Europe incorporating model uncertainty and spatial spillovers simultaneously). Furthermore, because several studies have shown that failure to account for spatial correlation effects in modeling technical efficiency can result in biased estimates of efficiency scores (e.g. Schmidt *et al.*, 2009), it is important to use an econometric framework for accommodating the presence of cross-sectional dependence in the observed regional production data.

In this context, our paper contributes to the literature on determinants of regional efficiency in two ways. On the one hand, to the best of our knowledge, this is the first paper that applies spatial stochastic frontier production functions to analyze technical efficiency of European regions.¹ We explicitly take into account spatial spillover effects by including a spatial lag term in the econometric frontier specification. While spatial versions of stochastic frontier models exist (see section 2), they still remain scarce and none concern the issue of regional production efficiency in Europe. Moreover, by merging techniques used in the stochastic frontier panel setting with spatial econometric techniques, we have developed two new spatial autoregressive production frontier panel data models where technical efficiency can be time-invariant or time-varying, in this last case permitting inefficiency to increase or decrease exponentially depending

¹ For non-spatial applications to the European case see, for example, Angeriz *et al.* (2006), Enflo and Hjertstrand (2009), or Ezcurra *et al.* (2008). These three papers address the issue of regional efficiency by means of the nonparametric Data Envelopment Analysis (DEA).

only on a scalar measuring the yearly rate of technological catch-up. These models extend the non-spatial estimators proposed by Battese and Coelli (1988, 1992) to the case where there is spatial dependence in the data.

The rest of the paper is structured as follows. Section 2 reviews the literature of stochastic frontier models with spatial dependence. The econometric methodology is then discussed in section 3, followed by the empirical application that contains a discussion of the sample data, the production function specification, and the main estimation results for production technology parameters and the efficiency ranking of individual regions. The final section summarizes and presents conclusions.

2. Frontier models with spatial dependence: A brief review of the literature

After the pioneer spatial autoregressive model by Cliff and Ord (1973), there has developed an extensive spatial econometrics literature dealing with interactions of economic units in space and over time (see, for example, the paper of Anselin, 2010, which describe the development of this field of spatial analysis during the past 30 years; spatial panel data models are discussed in detail in Baltagi, 2011, 2013, or in Elhorst, 2009, 2014). However, although the economic theory recognizes that spatial dependency can influence on the productivity of economic units (Acemoglu, 2009), the field of efficiency analysis generally does not take spatial interaction effects into account, notwithstanding evidence that efficiency improvements are one of the key components of productivity growth.

Only recent studies have tried to incorporate spatial dependence into frontier models. As a result, a new class of spatial frontier models has recently appeared in the productivity and efficiency analysis literature (see, e.g., Druska and Horrace, 2004; Schmidt *et al.*, 2009; Affuso *et al.*, 2010; Barrios and Lavado, 2010; Areal *et al.*, 2012; Pavlyuk, 2011, 2012, 2013; Brehm, 2013; Glass *et al.*, 2013, 2014, 2016; Fusco and Vidoli, 2013; Adetutu *et al.*, 2015; Ramajo *et al.*, 2015; Han *et al.*, 2016; Mastromarco *et al.*, 2016). We will next briefly review these papers in order to put the approach proposed in this paper into context.

Druska and Horrace (2004) is the first study in the literature on spatial frontier modeling. The authors develop a spatial error production frontier panel data model (an extension of the Kelejian and Prucha's, 1999 specification for cross-sectional data) which they estimate using the

Generalized Moments method using a sample of Indonesian rice farms, calculating time-invariant inefficiencies using the Schmidt and Sickles's (1984) method. They conclude that spillovers affect farm-level efficiency and ranking.

In Schmidt *et al.* (2009) a stochastic frontier model with a latent spatial structure is proposed to account for possible unknown geographical variation of the outputs of farms in Brazil. Their results demonstrate that models that ignore spatial effects produce significantly different ranking of inefficiencies across agents than those models that include the latent spatial effects.

In the context of impact evaluation programs that aim to increase efficiency and productivity of firms in developing countries, Affuso *et al.* (2010) propose a spatial autoregressive stochastic production model that estimates the technical efficiencies of matched subsamples of treated and control farmers in rural areas of Tanzania. Their article extends the literature addressing the presence of self-selectivity bias considering both the issue of spatial autocorrelation and the problem of sample selection

Barrios and Lavado (2010) propose an augmented stochastic frontier model that includes a sparse autoregressive component in the cross-section case, accounting for spatial externalities in the production capacity of the producers, or a spatial-temporal component for a panel data, where information on both temporal dependencies and the interaction among units at specific points of time is present. Using two data sets for Philippines, the authors show that these components can improve estimates of technical efficiency in a production frontier that is usually biased downwards.

Areal *et al.* (2012) incorporate spatial dependence into stochastic frontier analysis using an autoregressive specification for the inefficiency component of a compound error term, and employ this method to analyze technical efficiency of a sample of dairy farms in England and Wales. Their results suggest that there is spatial dependence in technical efficiency in the analyzed units, and not accounting for it may produce biased results for the efficiency distribution.

Pavlyuk (2011, 2012, 2013) develops spatial modifications of the standard stochastic frontier model that include spatial lags, spatial autoregressive disturbances and spatial autoregressive inefficiencies. Maximum Likelihood (ML) estimators are derived for some of these models, and small sample properties are investigated with a set of Monte Carlo experiments. Also the ML

estimators are tested with real-world data sets of regional tourism markets in the Baltic States and of the European airports; in all the empirical applications significant spatial components in data are discovered. The main conclusion is that non-inclusion of spatial components into frontier models can lead to significant biases of frontier parameters and efficiency levels estimates.

Brehm (2013) analyzes the potential link between fiscal decentralization and economic efficiency for a panel of counties from a Chinese province based on a stochastic frontier model with spatial error correction. The paper examines in addition the role of an estimation bias due to spatial and serial correlation. The results point to the significance of the benchmarking or competition effect, this effect identifying the spatially interdependent allocation of public investments as a major source for differences in inefficiency at the county level.

Glass *et al.* (2013, 2014) introduce the concept of efficiency spillover, extending the non-spatial Cornwell *et al.*'s (1990) model to the case where there is spatial autoregressive dependence. On the other hand, Glass *et al.* (2016) use a composed error structure by assuming a half-normal distribution for inefficiency. Their approach permits the analyst to benchmark how successful units are at exporting and importing productive performance to and from other units. Features of the modeling include time-varying efficiency and estimation of own and spillover returns to scale. The model is applied to aggregate production in European countries and state-level manufacturing costs in the US, highlighting in all cases the asymmetry between efficiency spillovers to and from a decision-making unit.

As in Areal *et al.* (2012), Fusco and Vidoli (2013) include a spatial lag in the inefficiency term of the compound error term to allow the splitting of the inefficiency into a spatial component and into a specific term for every firm. The proposed model is applied to cross-sectional data from the agricultural sector in Italy. The results show the effectiveness of the proposed technique on data with uniform and strong spatial dependence, and on data that show only some local interdependencies.

Adetutu *et al.* (2015) propose a local spatial stochastic frontier model that accounts for spatial interaction by allowing spatial lags of the inputs and spatial lags of the exogenous variables to shift the production frontier technology. Then, the frontier analysis is different from that in Glass *et al.* (2013, 2014, 2016), where global spatial dependence is permitted via a spatial lag of

the dependent variable; moreover, rather than calculate efficiency from the cross-sectional specific effects, they calculate efficiency by making an assumption about the distribution of the inefficiency component of the error term.

In Ramajo *et al.* (2015), a nonparametric robust partial frontier methodology is applied to account for the presence of geographical externalities. Specifically, a spatial autoregressive term is included as an external factor in a Conditional Order- m model (Cazals *et al.*, 2002; Daraio and Simar, 2005), permitting the testing of the hypothesis of non-separability (the factor impacts both the input-output space and the distribution of efficiencies). The results show that geographical externalities affect both the frontier level and the probability of being more or less efficient. Specifically, the results support the fact that the spatial autoregressive term has an inverted U-shaped non-linear impact on the performance of regions.

Han *et al.* (2016) investigate spillover effects of public capital stock in a production function model that accounts for spatial dependencies. They use the Schmidt and Sickles's (1984) hypothesis of time-invariant inefficiency, but permit global spatial dependence by introducing a spatial autoregressive term. Using data for 21 OECD countries from 1960 to 2001, they found that spillover effects can be an important factor explaining variations in technical inefficiency across countries as well as discrepancies among various levels of output elasticity of public capital in traditional production function approaches.

The last contribution in this small body of literature on spatial frontier modeling is Mastromarco *et al.* (2016) who proposes a unified framework for accommodating both time and cross-sectional dependence (strong and weak) in modeling technical efficiency in panel stochastic frontier models by combining an unobserved common factors-based approach and a threshold efficiency regime selection mechanism. The proposed approach is applied to a dataset of 26 OECD countries, providing estimation results for the production technology parameters and the associated efficiency ranking of individual countries. The results show a positive spillover effect on efficiency, and also permit to identify efficiency clubs endogenously (a technology club, with countries on or near the frontier, and an inefficiency club, with countries below the frontier).

3. Econometric methodology: Spatial autoregressive stochastic frontier production models for regional panel data

The aggregate production frontier approach has been used in the cross-country literature to show that economic growth convergence can be viewed as countries' movements over time toward the world or partial-world economy frontiers (efficiency improvements), and to estimate total factor productivity growth, technical progress, and technological catch-up (see, among others, Kumar and Russell, 2002; Kneller and Stevens, 2003; Henderson and Russell, 2005; Kumbhakar and Wang, 2005; Arestis et al., 2006; Henry *et al.*, 2009; Afonso and Aubyn, 2010; ; Growiec, 2012; Christopoulos and McAdam, 2015).

The production function method has also been used to analyze regional growth in the United States (e.g., Brock and Ogloblin, 2014) and Europe (e.g., Ezcurra et al., 2008). In this case, the frontier approach assumes that a region is technically efficient if it produces the maximum feasible output from a given combination of inputs and technology, regardless of market demand and prices. On the other hand, it assumes that if a region produces less than is technically feasible given both technology and inputs, it is inefficient. Hence, inefficiency is measured as the distance of each individual observation from the frontier.

Following the same methodology of Brock and Ogloblin (2014), in this paper we use the stochastic production-frontier approach to analyze technical efficiency in European regions. This method is extended by introducing a spatial autoregressive term to control for spatial spillover effects that can exist due to cross-regional interdependence. In the next section, we will outline the proposed spatial stochastic frontier model.

Stochastic production frontier analysis

Aigner *et al.* (1977) and Meeusen and van den Broeck (1977) pioneered a stochastic production frontier method to estimate potential output and efficiency characteristics.² In stochastic frontier analysis (SFA), a production econometric specification is proposed as:

$$(1) \quad Y_i = F(\tilde{\mathbf{X}}_i, \boldsymbol{\beta}) e^{\nu_i} T E_i$$

where Y denotes observed output, $Y_i^* = F(\tilde{\mathbf{X}}_i, \boldsymbol{\beta})$ represents the maximum quantity of output that can be produced from a given K -dimensional input bundle $\tilde{\mathbf{X}} = (X_1, X_2, \dots, X_K)$, $\boldsymbol{\beta}$ is the vector of

² Greene (2008) provides excellent discussions of the development of the field.

parameters of the production function to be estimated, v_i is a stochastic disturbance term allowing for unobserved random errors affecting the frontier (exogenous production shocks), and $0 < TE_i = Y_i/Y_i^* = e^{-u_i} \leq 1$ is the Farrell (output oriented) measure of technical efficiency, $u_i \geq 0$ being a measure of the degree of inefficiency in the resource allocation in economic unit i .

The reformulated stochastic frontier (SF) log production model is given by:

$$(2) \quad \log Y_i = f(\tilde{\mathbf{X}}_i, \boldsymbol{\beta}) + v_i - u_i$$

and then the stochastic frontier is given by $f(\tilde{\mathbf{X}}_i, \boldsymbol{\beta}) + v_i$, and u_i represents the inefficiency component (see figure 1).

[insert figure 1 about here]

Spatial versions of the cross-sectional SF model (SpSF models)

Using a log-linear functional form approximation for the function f (the log of the production function F) the standard SF model can be written as:

$$(3) \quad y_i = \mathbf{x}_i' \boldsymbol{\beta} + v_i - u_i$$

where y_i represents the logarithm of the output of region i , and \mathbf{x}_i is a $K \times 1$ vector containing the logarithms of the inputs (and possibly high-order transformations of them, squared and cross-product terms). Note that this model does not include any type of spatial dependence, a potentially restrictive specification in empirical applications where geo-referenced data are used because there is a high probability that these types of data show some form of spatial autocorrelation.

Expressing the aspatial SF model $y_i = \mathbf{x}_i' \boldsymbol{\beta} + v_i - u_i$ in matrix form,

$$(4) \quad \mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \mathbf{v} - \mathbf{u}$$

Pavlyuk (2011, 2012, 2013) proposes a general spatial frontier model for cross-section data defined by the following equations:³

³ The terms between brackets in equation (5) are not proposed in the original papers of Pavlyuk but we introduced them following earlier literature modeling inefficiency in terms of exogenous determinants and their spatially lagged values (see Section 2).

$$\begin{aligned}
(5) \quad & \mathbf{y} = \rho \mathbf{W}_1 \mathbf{y} + \mathbf{X} \boldsymbol{\beta} + (\mathbf{W}_2 \mathbf{X}) \boldsymbol{\gamma} + \boldsymbol{\varepsilon} \\
& \boldsymbol{\varepsilon} = \boldsymbol{v} - \mathbf{u} \\
& \boldsymbol{v} = \xi \mathbf{W}_3 \boldsymbol{v} + \tilde{\boldsymbol{v}} \\
& \mathbf{u} = \eta \mathbf{W}_4 \mathbf{u} + [\mathbf{Z} \boldsymbol{\delta} + (\mathbf{W}_5 \mathbf{Z}) \boldsymbol{\omega}] + \tilde{\mathbf{u}}, \mathbf{u} \geq \mathbf{0}
\end{aligned}$$

where \mathbf{W}_j are spatial weights matrices with rows $\mathbf{w}_{j,i}$ specifying the spatial connections of each unit i according to some measure of proximity between the units. This general unrestricted specification, introducing spatial lags of the inputs-output vectors, spatial errors, and spatial inefficiency terms, is a very flexible specification but raises computational problems due to identification problems. This is the reason because finally only two spatial stochastic frontier models are considered in the applications, a spatial autoregressive one and a spatial autoregressive model with spatial autoregressive disturbances.

Panel versions of SpSF models

The frontier models we have discussed to this point have been mainly applied for analysis of cross-sectional data. Since our application uses a panel of European regions, we need to re-adapt the above formulation for the case of panel data. The fundamental challenge is to relax some of the assumptions that the cross-sectional SF model imposes, basically considering a realistic characterization of the evolution of inefficiencies over time (see Kumbhakar *et al.*, 2014, for a recent review of competing non-spatial panel data frontier models).

In a non-spatial context, Battese and Coelli (1988) (BC88) extended model (3) to panel data, proposing the following SF model:

$$\begin{aligned}
(6) \quad & y_{it} = \mathbf{x}'_{it} \boldsymbol{\beta} + \varepsilon_{it} \\
& \varepsilon_{it} = v_{it} - u_i \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_i \sim N^+(\mu, \sigma_u^2)
\end{aligned}$$

This formulation assumes that the (time-invariant) inefficiency term follows a non-negative truncated-normal distribution that is truncated at zero with mean μ and variance σ_u^2 , and the idiosyncratic error follows a standard symmetric normal distribution $v_{it} \sim N(0, \sigma_v^2)$.

Battese and Coelli (1992) (BC92) proposed an alternative (also non-spatial) model with unit-specific time-varying decay pattern of variation of inefficiency:

$$\begin{aligned}
(7) \quad & y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \\
& \varepsilon_{it} = v_{it} - u_{it} \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_{it} = h(t)u_i
\end{aligned}$$

where $h(\cdot)$ is the deterministic function $\exp(-\eta(t - T))$ and u_i is a non-negative truncated-normal distribution given by $u_i \sim N^+(\mu, \sigma_u^2)$.⁴ When $\eta = 0$, the model BC92 (time-varying decay) reduces to the model BC88 (time-invariant).

We extend the non-spatial BC88 and BC92 models by generalizing their respective panel specifications following the same approach used by Pavlyuk (2011, 2012, 2013) for the cross-sectional case. In particular, a first-order spatial autoregressive -SAR(1) - term have been added to models (6) and (7) allowing for the existence of substantive spatial autocorrelation between neighboring units.⁵ Hence, it is now possible to obtain spatial lag frontier models as follows:

$$\begin{aligned}
(8) \quad & y_{it} = \rho \mathbf{w}'_i \mathbf{y}_t + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \\
& \varepsilon_{it} = v_{it} - u_i \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_i \sim N^+(0, \sigma_u^2)
\end{aligned}$$

for the BC88 case, and

$$\begin{aligned}
(9) \quad & y_{it} = \rho \mathbf{w}'_i \mathbf{y}_t + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \\
& \varepsilon_{it} = v_{it} - u_{it} \\
& v_{it} \sim N(0, \sigma_v^2) \\
& u_{it} = \exp(-\eta(t - T)) u_i, \quad u_i \sim N^+(\mu, \sigma_u^2)
\end{aligned}$$

for the BC92 model, where the vectors \mathbf{w}_i of known positive constants specify the strength of the spatial connections of each unit i according to some measure of proximity between the economic units, and ρ is the spatial autoregressive parameter.

⁴ Feng and Serletis (2009) have extended the BC formulation by specifying $h(t) = \exp(-\eta_1(t - T) - \eta_2(t - T)^2)$ in a cost function context. In the same way, Kumbhakar (1991) proposes the function $(1 + \exp(\gamma_1 t + \gamma_2 t^2))^{-1}$ that can be monotonically increasing (decreasing) or concave (convex). On the other hand, Cornwell et al. (1990) proposes an alternative model that assumes $u_{it} = \omega_{1i} + \omega_{2i}t + \omega_{3i}t^2$ allowing a unit-specific temporal pattern of inefficiency but requiring the estimation of a large number of parameters. Glass *et al.* (2013, 2014) have adapted this last model for the spatial panel data case.

⁵ Because in our application we are more interested to measure the spillover effects between regions, we only introduce a spatial autoregressive term but we do not model spatial dependence in the error process v_{it} (as in Druska and Horrace, 2004). The consideration of a mixed regressive spatial autoregressive specification will be the objective of future research.

Both models will be the basis for the empirical application presented in the next section. The main difference between them centers on the hypothesis of time-invariance of technical efficiency in model (8), which can be tested through the statistical significance of the decay parameter η in the exponential function of model (9). If the null hypothesis is rejected, technical efficiency of regions can increase or decrease exponentially depending of the sign of the decay parameter η : when $\eta > 0$, this implies that the degree of inefficiency decreases over time, and units move towards the frontier (technological catch-up) at a rate of $(100 \times \eta)\%$ per year; if $\eta < 0$, technical inefficiency increases exponentially and this implies divergence (technical inefficiency is growing).

Comparing the second proposed model with earlier contributions in the spatial stochastic frontier literature (see section 2), our proposal represents an alternative to other specifications that allows efficiency to vary over time and over the cross-section. Hence, rather than assume cross-sectional specific effects in a SAR stochastic frontier model (Glass *et al.*, 2013, 2014), or that the inefficiency distribution is half-normal (Glass *et al.*, 2016), we use a time-varying decay efficiency specification.

4. Empirical application: Technical efficiency of European regions

Sample data

The data set used in the analysis is a balanced annual panel with 120 Nomenclature of Territorial Units for Statistics 2 (NUTS-2) regions in nine EU member states, namely Austria (AT), Belgium (BE), France (FR), Germany (DE), Italy (IT), Netherlands (NL), Portugal (PT), Spain (ES) and Sweden (SE) for the period 1995-2007 (see figure 2).

[insert figure 2 about here]

The aggregate data for European regions have been retrieved from the BD.EURS database recently built by Escribá and Murgui (2014a, b). This database contains information at the NUTS-2 level about the regional production Y –measured as gross value added, GVA, at constant 2000 market prices - and two inputs, physical capital (K) and human capital (L), measured as total regional capital stock -private and public - (at constant 2000 prices) and total regional labor force (represented by employed people in all NACE activities), respectively. The

BD.EURS regional database has been built using information about gross value added, gross fixed capital formation and employment from three different sources: REGIO-EUROSTAT for the regional information, and AMECO and EU-KLEMS for the national sources.⁶

Econometric model specification

We start the empirical analysis by hypothesizing the existence of a regional Cliff-Ord-type production frontier function which include a variable capturing the interaction between economic units (the spatial lag of the neighbor's output):⁷

$$(10) \quad Y_{it} = F \left(\sum_{j=1}^N w_{ij} Y_{jt}, K_{it}, L_{it} \right) e^{g(t)} e^{v_{it}} e^{-u_{it}}$$

where Y denotes output, K , L represent physical capital and labor respectively, F and g represent the production and technical progress functions, and subscripts $i=1,2,\dots,N$ and $t=1,2,\dots,T$ respectively index region and time.

In our application, because of its higher flexibility with respect to the *Cobb–Douglas* production function widely used in the related literature, we consider that the functional form for the (log) production function takes the form of a spatially-augmented *translog* functional form in terms of the logarithms of K and L (Christensen et al., 1973);⁸ in addition, we consider that the technical progress function can be a non-linear function of a time trend variable. Hence, the SAR(1) stochastic frontier model is specified as follows:⁹

⁶ See Escrivá and Murgui (2014b) for details and descriptive statistics of the variables.

⁷ The corresponding spatial autoregressive parameter, measuring the relevance of spillovers across cross-sectional units, indicates the direction of the global spatial externalities that the data show (Anselin, 2003): greater this parameter –in absolute terms– much more the output of each economic unit will depends on the output of its neighbors.

⁸ As a robustness exercise we also consider a *Fourier* functional form that adds trigonometric terms of re-scaled values of the original variables to the *translog* production function in order to achieve a more global approximation to the true frontier (Gallant, 1981, 1982). The efficiency estimates were very similar to the *translog* case so we omit these complementary results.

⁹ As we are aware that subject-specific effects are an important source of heterogeneity in stochastic frontier models (Greene, 2002, 2005; Chen *et al.*, 2014), we also estimated a country fixed-effects frontier model changing the constant intercept α_0 by country-specific intercepts, $\alpha_0 + \mathbf{c}'\boldsymbol{\alpha}$, where \mathbf{c} is a vector of dummy variables for eight of the nine EU countries which regions belong (Germany was used as the base country). This variant yielded similar estimation results to the obtained with the base model and is not presented here. More general specifications that include economic, political of socio-cultural indicators of regions have not been estimated due to information

(11)

$$y_{it} = \alpha_0 + \rho \sum_{j=1}^N w_{ij} y_{jt} + \beta_1 k_{it} + \beta_2 l_{it} + \beta_3 k_{it}^2 + \beta_4 l_{it}^2 + \beta_5 k_{it} l_{it} + \delta_1 t + \delta_2 t^2 + v_{it} - u_{it}$$

where y_{it} , k_{it} and l_{it} are the log of the output, the physical capital, and the human capital, respectively; t is a time trend; the stochastic noise component v_{it} it is a idiosyncratic term assumed to be *i.i.d.* normal with zero mean and constant variance, $v_{it} \sim N(0, \sigma_v^2)$, to allow for unobserved random errors affecting the frontier; and u_{it} represents inefficiency.

For each region, the endogenous spatial lags of the dependent variable are built as $\sum_{j=1}^N w_{ij} y_{jt}$, with elements w_{ij} reflecting the spatial connectivity structure between regions and the strength of the relationships across them, and satisfying the restrictions $w_{ij} \geq 0$, $w_{ii} = 0$ and $\sum_{j=1}^N w_{ij} = 1$. In our case, the weights matrix \mathbf{W} is the row-standardized version of the geographic weight matrix \mathbf{C}_d in which elements c_{ij} have been defined based on inverse distances with a decay factor $c_{ij} = \frac{1}{d_{ij}^\phi}$ where d_{ij} denotes the physical distance between regions i and j , and ϕ is the distance decay parameter. Although ϕ can be estimated by nonlinear estimation techniques, we have used particular values as usual in the literature (see, for example, Crespo-Cuaresma *et al.*, 2014, Glass *et al.*, 2016). Specifically, we used alternative values $\phi = 1$ and $\phi = 2$, and the results were very similar. This is the reason because from now on we will present the empirical results using $\phi = 1$, that to say, we will use in the calculations the inverse distance specification, $c_{ij} = \frac{1}{d_{ij}}$, and the corresponding row-normalized exogenous, symmetric and dense spatial weights matrix \mathbf{W} .

The proposed empirical frontier model also allows cross-section heterogeneous inefficiency terms $u_{it} \geq 0$. In our application, two models have been estimated depending of the properties assumed for the technical inefficiency term:

- Case 1 (Time-invariant inefficiency): $u_{it} = u_i \sim N^+(\mu, \sigma_u^2)$ is a non-negative stochastic term measuring the distance from the frontier for each region, and following a truncated-normal distribution (Battese and Coelli, 1988).

restrictions of our database. The specification of a general region-specific fixed or random effects frontier model that allows time-invariant heterogeneity in the frontier production function will be an area of future research.

- Case 2 (Time-varying inefficiency): $u_{it} = h(t)u_i$, where $h(t) = \exp(-\eta(t - T))$ and u_i is a non-negative stochastic term given by $u_i \sim N^+(\mu, \sigma_u^2)$ (Battese and Coelli, 1992).¹⁰

Both formulated models, containing spatial interaction effects, non-linear technical progress and heterogeneous time-varying technical efficiency, have been estimated using the Maximum Likelihood (ML) method taking into account the endogeneity of the spatial lag variable, and the efficiency estimation procedure involves three sequential steps: in the first step, the parameters of the frontier model were estimated maximizing the log-likelihood function; after that, point estimates of inefficiency were obtained through the usual conditional expectation method, $\hat{u}_{it} = E[u_{it}|\varepsilon_{it}]$ (Jondrow *et al.*, 1982); finally, consistent estimates for the technical efficiency of the i^{th} region at time t were calculated as $\hat{\tau}_{it} = \exp(-\hat{u}_{it})$.

Discussion of the stochastic frontier and efficiency results

In this section, we focus on the issue of the productive performance of 120 NUTS-2 regions in nine European countries over the period 1995-2007. In a cross-regional framework, production inefficiencies can be identified as the distance of the individual region's production from the frontier. Hence, efficiency improvement will represent productivity catch-up via technology diffusion because inefficiencies can reflect a sluggish adoption of new technologies (Ahn and Sickles 2000).

Productivity catching-up among European regions has been an important topic of interest for many researchers (e.g. Gardiner *et al.*, 2004, Ezcurra *et al.*, 2007). In particular, it is important to see how the productivity of European regions evolves over time because the literature indicates that regional differences in productivity are the main reason for regional growth and per capita income inequality in the EU (e.g. López-Bazo *et al.*, 1999, Cuadrado-Roura *et al.*, 2000). In this sense, figure 3 presents the quantile maps of output per worker in 1995 and 2007 obtained from our database, based on the associated Moran's scatterplots, and figure 4 presents the usual absolute β -convergence graph (first panel) for the labor productivity variable –labor productivity

¹⁰ In the present version of the paper a constant mean and variance of the distribution of the inefficiency term is assumed. This limitation would be avoided specifying the mean and the variance as a function of vectors of time-invariant covariates (or the means of time-varying covariates for each region) as $\mu_i = \delta_0 + \zeta \mathbf{w}'_i \mathbf{u} + \mathbf{z}'_{m,i} \boldsymbol{\delta}$ and $\sigma_{u,i}^2 = \exp(\omega_0 + \mathbf{z}'_{v,i} \boldsymbol{\omega})$. Consideration of these extensions will be the immediate objective of future research.

growth 1995-2007 [y-axis] versus labor productivity in 1995 [x-axis]- and the Theil's inequality index for this variable over the complete period 1995-2007 (second panel).¹¹

The maps in figure 3 show a strong geographic pattern in the European regional data about output per worker¹² (the values of the Moran's I statistics reveal the existence of a strong positive and statistically significant degree of spatial dependence in the distribution of European productivity), and also suggest the presence of spatial heterogeneity in the form of two spatial clusters of high and low productive regions: the high-productivity cluster situated in Europe's economic core area, the "Blue-Banana" zone (Brunet, 2002; Hospers, 2002), from the West of England in the north to North of Italy in the south; and the low-productivity cluster including some of the least developed region or Europe (located in Portugal, Spain, Southern Italy and Eastern Germany).

The graphs in figure 4 shows that there has been unconditional β -convergence in labor productivity (the slope of the regression was negative and statistically significant), and that regional inequality in productivity decreased between 1995 and 2007. Indeed, the index values fell over 8.5 percent over the thirteen years considered although, as can be seen, the reduction has not been uniform throughout the period (the main decrease take place in the late nineties and the early twentieth century).

[insert figures 3 and 4 here]

On the other hand, because productivity growth is the net change in output due to changes in efficiency and technical change, efficiency is a component of productivity. In fact, the results in Ezcurra and Irázoz (2009) show that regional differences in the levels of technical efficiency account for a relatively important portion of spatial inequality in labor productivity within the EU. Then, it is a relevant question to analyze the degree of efficiency with which the European regions use its available resources in production.

Following the spatial stochastic frontier analysis presented in section 3, now we will present the efficiency estimates obtained for the EU regional panel database used in this work. However,

¹¹ We used the measure of inequality proposed by Theil (1967), $T_0(S_t) = \sum_{i=1}^n f_{it} \log\left(\frac{\mu_t}{S_{it}}\right)$, where f_{it} is the share in total production of region i , S_{it} is the value of the analyzed variable, S , in region i , and μ_t stands for the weighted average of the variable S over space, all variables measured at time t .

¹² Investigating the sources of regional growth in Europe, López-Bazo *et al.* (2004) showed that regional productivity spillovers are far from negligible, and may cause non-decreasing returns at the spatial aggregate level.

before analyzing the efficiency results, we will present and discuss the econometric results for the selected frontier models. In table 1, we present the maximum-likelihood estimates obtained for the spatial stochastic frontier models defined by equations (8) and (9) using the production function given by (11).

[insert table 1 here]

We first have tested the null hypothesis about inefficiency change over time, $H_0: \{\eta = 0\}$ vs. $H_1: \{\eta \neq 0\}$. The null hypothesis was clearly rejected (p -value=0.0000), and the estimate of η , 0.008, implies technological catch-up: European regions have been converging to the frontier at a rate of 0.8% per year, meaning that technical inefficiency has been shrinking at 0.8 percent points per year.¹³ Due to the significance of the estimated of η , from now on we will only consider in our analysis the Case 2 of our econometric specification, that is to say, the time-varying inefficiency production frontier model (column 3 in table 1).

Secondly, with respect to the spatial autoregressive parameter (ρ), the obtained estimate (0.35) is positive and statistically significant at much more than 1% level (p -value=0.0000), indicating the relevance of externalities (such as technological interregional spillovers or factor mobility) in order to explain the productive process of each region. On the other hand, the estimates of ρ from the Case 1 and Case 2 models are of similar order of magnitude, which indicates that the degree of global spatial dependence of regional output (y) is robust to the specification of the technical inefficiency term.¹⁴

Finally, all the parameters of the translog function (β 's) and also the trend parameters (δ 's) are statistically significant at more that the 1% level (in all cases the p -value equals 0.0000). Moreover, the Cobb-Douglas production specification (which impose the restrictions $\beta_3 = 0$, $\beta_4 = 0$, and $\beta_5 = 0$ on equation 12) was clearly rejected by the data (p -value=0.0000). On the other hand, the statistical significance of the δ 's indicates that the production frontier shifted appreciably over the considered period according to the values of the estimated parameters, $\hat{\delta}_1 = -0.011$, and $\hat{\delta}_2 = 0.0002$.

¹³ Our estimate contrasts with the value of 2.4% obtained by Kumbhakar and Wang (2005) using a non-spatial stochastic production model for a sample of 82 countries over the period 1960-1987.

¹⁴ This result is similar to that obtained by Glass *et al.* (2016) using aggregate data for 41 European countries for the period 1990-2011, and several spatial stochastic frontier specifications.

Now we turn to analyzing the efficiency results. First, in table 2 we present the summary statistics of the regional technical efficiency estimates over the full sample (EU-9 1995-2007), over space (mean values of efficiency for each country over the whole sample period), and over time (year by year from 1995 to 2007).¹⁵ Figure 5 presents the kernel density distribution of the estimates over the full sample (1,560 observations), and figure 6 shows the mean (first panel), and the median, 0.25 and 0.75 quantile scores per year (second panel), this second graph revealing the spread of the efficiency values, measured by the inter-quantile range.

[insert table 2 here]

[insert figures 5 and 6 here]

Looking at second line of table 2, we can observe that full sample average technical efficiency is around 0.68, this value implying that the average EU-9 regional efficiency could be increased by 32% if inputs were used in their most efficient combination. On the other hand, the graph in figure 5 suggests the possibility of uni-modality in the distribution of the full sample technical efficiency estimates. In fact, the Silverman nonparametric test for multimodality (Silverman, 1981) was applied and the null of uni-modality was not rejected (p -value=0.96). Hence, our results suggest that there has not been polarization across European regions in terms of technical efficiency. In other words, there are no spatial convergence clubs in the distribution of technical efficiency of the European regions.

Additionally, with the “over space” country information contained in table 2 it is possible to categorize the EU-9 countries in terms of their estimated 1995-2007 average values of technical efficiency: Austria, Germany and Portugal present values below the EU-9 mean (0.68); Spain, France, Italy, Netherlands and Sweden show values clustered around the average; and, finally, only Belgium exhibits a value (0.75) clearly above the EU-9 mean.¹⁶

Finally, the “over time” numerical information of table 2, with the graphs contained in figure 6, show that the degree of average regional efficiency has increased steadily year by year. Overall, this result shows that European regions have converged during the 1995-2007 period in terms of their ability to utilize physical capital and labor to produce GVA.

¹⁵ Detailed results for individual efficiency for the 120 EU-9 regions can be obtained from the authors upon request.

¹⁶ Our mean-country results can be compared with those obtained by Mastromarco *et al.* (2013) by combining a dynamic efficiency analysis in the stochastic frontier framework, using a dataset of 18 EU countries over 1970-2004 (see table 3, where efficiency results are showed over the two sub-periods 1970-1995 and 1996-2004)

Figure 7 presents the histogram of the mean regional efficiency scores (averaged for the 1995 to 2007 period) of individual regions, showing the frequency distribution of the estimations. Additionally, figures 8 and 9 show, respectively, the quantile map of the regional scores (dark-shaded regions can be considered as comparatively more efficient than light-shaded regions) and the associated Moran's scatterplot and I statistic, and the LISA maps (Anselin, 1995) of regional technical efficiency mean estimations.

[insert figures 7, 8 and 9 here]

Looking at figure 8, the quantile map points to a significant positive spatial dependency between the efficiency level of each region and the performance of their neighboring regions. This hypothesis is confirmed by the Moran's I statistic ($I=0.2055$), which indicates the presence of a strong geographic pattern (p -value=0.001). Moreover, the LISA maps of the EU-9 regional mean efficiency scores of figure 9 show that there are two spatial clusters of European regions: the first cluster (red color) is characterized by high annual average scores (more efficient regions) surrounded by regions with similar results (*high-high* zone in the terminology of the spatial econometrics literature); the second cluster (blue color) includes more inefficient regions (*low-low* zone).

Finally, in order to explore the relative contribution of the technical efficiency component (change of the obtained efficiency scores) to labor productivity growth, figure 10 presents the regression line graph between these variables. The corresponding slope coefficient is positive and statistically significant (p -value=0.0077), which is an indication that a non-negligible part of European regional productivity growth 1995-2007 can be attributed to changes in technical efficiency.

6. Final remarks and conclusions

Trying to explore the potential role of variations in regional technical efficiency as a contributing factor in providing explanation for convergence or divergence in Europe, our paper estimates a spatial stochastic frontier model that captures global spillovers through the introduction of a spatial autoregressive term in the assumed *translog* production technology. Since the spatial frontier model is applied to an aggregate production function using balanced panel dataset of 120 European regions (in 9 EU member states) over the period 1995-2007, we propose a panel

stochastic frontier model that allows the efficiency effects to vary over time and between cross-sectional units, also allowing for non-linear exogenous technological change. Specifically, we have ‘spatialized’ the BC (1992) model, which involves using an inefficiency term with time-varying factor and time-invariant characteristics (the special case of time-invariant factor produce the non-spatial BC model, 1988). The derived global spatial stochastic frontier model is estimated using maximum likelihood methods taking into account the endogeneity of the spatial lag variable included in the econometric specification.

Using the European regional dataset, we provide satisfactory estimation results for the production technology parameters, the inefficiency time-varying factor, and the associated technical efficiency scores of individual regions. We find statistically significant and positive global spillover effects, showing that geographical externalities affect the EU frontier and therefore play an important role in regional growth and convergence in Europe, and also we find that regions have been converging to the EU-9 technology frontier at a statistically significant rate of 0.8% per year.

Furthermore, our descriptive analysis of the technical efficiencies reveals cross-sectional dependence in the estimated scores, showing the dependency of a region’s efficiency with the performance of its neighbors. This finding suggests two areas for future work: to extend the spatial stochastic frontier models formulated in this paper (which can only accommodate the weak form of spatial dependence) for more general specifications which can generate strong and/or weak forms of cross-sectional dependence endogenously, for example following the approach proposed by Mastromarco *et al.* (2016) for modeling the time-varying inefficiency term; to estimate efficiency spillovers to and from a region explicitly, for example using the method proposed by Glass *et al.* (2016) to calculate time-varying relative direct, relative indirect and relative total efficiencies in order to analyze spatial efficiency.

REFERENCES

- Acemoglu, D. 2009. *Introduction to Modern Economic Growth*. Princeton University Press, Oxford.
- Adetutu, M., Glass, A.J., Kenjegalieva, K., and R.C. Sickles. 2015. The effects of efficiency and TFP growth on pollution in Europe: a multistage spatial analysis. *Journal of Productivity Analysis* 43 (3): 307–326.
- Affuso, E. 2010. Spatial Autoregressive Stochastic Frontier Analysis: An Application to an Impact Evaluation Study. Available at SSRN: <http://ssrn.com/abstract=1740382>.
- Afonso, A., and M.St. Aubyn. 2010. Public and private inputs in aggregate production and growth: A cross-county efficiency approach. Working Paper Series No. 1154, European Central Bank (ECB), Germany. Available at SSRN: <http://ssrn.com/abstract=1551199>.
- Ahn, S. C., and R.C. Sickles. 2000. Estimation of long-run inefficiency levels: A dynamic frontier approach, *Econometric Reviews* 19: 461-492.
- Aigner, D., C. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6 (1): 21-37.
- Angeriz, A., McCombie, J., and M. Roberts. 2006. Productivity, efficiency and technological change in European Union regional manufacturing: A data envelopment analysis approach, *The Manchester School* 74 (4): 500–525.
- Anselin, L. 1995. Local indicators of spatial association – LISA. *Geographical Analysis* 27 (2): 93-115.
- Anselin, L. 2003. Spatial Externalities, Spatial Multipliers, and Spatial Econometrics. *International Regional Science Review* 26 (2): 153-166.
- Anselin, L. 2010. Thirty years of spatial econometrics. *Papers in Regional Science* 89 (1): 3-25.
- Areal F.J., Balcombe K., and R. Tiffin. 2012. Integrating spatial dependence into Stochastic Frontier Analysis. *The Australian Journal of Agricultural and Resource Economics* 56: 521-541.
- Arestis, P., Chortareas, G., and E. Desli. 2006. Financial development and productive efficiency in OECD countries: An exploratory analysis. *The Manchester School* 74 (4): 417-440.
- Baltagi, B.H., 2011. Spatial panels. In: Ullah, A., and D.E.A. Giles (Eds.), *Handbook of Empirical Economics and Finance*. Chapman & Hall/CRC, Florida.
- Baltagi, B.H., 2013. *Econometric Analysis of Panel Data*. Wiley, Chichester.
- Barrios E.B., and Lavado R.F. 2010. *Spatial Stochastic Frontier Models*. Discussion Paper Series No. 2010-08, Philippine Institute for Development Studies, Philippines.
- Barro RJ, and X. Sala-i-Martin. 1991. Convergence across states and regions. *Brooking Papers of Economic Activity* 1:107–158
- Battese, G. E., and T. J. Coelli. 1988. Prediction of firm-level technical efficiencies with a generalized frontier production function and panel data. *Journal of Econometrics* 38 (3): 387-399.
- Battese, G. E., and T. J. Coelli. 1992. Frontier production functions, technical efficiency and panel data: With application to paddy farmers in India. *Journal of Productivity Analysis* 3: 153-169.
- Baumol W.J. 1986. Productivity growth, convergence, and welfare: what the long-run data show. *American Economic Review* 76: 1072–1085.
- Brehm, S. 2013. Fiscal incentives, public spending, and productivity – County-level evidence from a Chinese province. *World Development* 46: 92-103.

- Brock, G., and C. Oglobin. 2014. Another look at technical efficiency in American states, 1979-2000. *Annals of Regional Science* 53: 577-590.
- Brunet, R. 2002. Lignes de force de l'espace européen. *Mappemonde* 66: 14-19.
- Caselli, F. 2005. Accounting for cross-country income differences. In: Aghion, P., and S. Durlauf (Eds.), *Handbook of Economic Growth*. Elsevier, Amsterdam.
- Cazals, C., Florens, J.P., and Simar, L. 2002. Nonparametric frontier estimation: A robust approach. *Journal of Econometrics* 106 (1): 1-25.
- Chen, Y.Y., Schmidt, P., and Wang, H.J. 2014. Consistent estimation of the fixed effects stochastic frontier model. *Journal of Econometrics* 181 (2): 65-76.
- Christensen, L., Jorgenson, D., and L. Lau. 1973. Transcendental logarithmic production frontiers. *Review of Economics and Statistics* 55:28-45.
- Christopoulos, D., and P. McAdam. 2015. Efficiency, inefficiency and the MENA frontier. Working Paper Series No. 1757, European Central Bank (ECB), Germany.
- Cliff, A.D., and J.K. Ord. 1973. Spatial Autocorrelation. In: *Monographs in Spatial and Environmental Systems Analysis*, Volume 5. London: Pion, 1973.
- Cornwell, C., Schmidt, P., and R.C. Sickles. 1990. Production frontiers with cross-sectional and time-series variation in efficiency levels. *Journal of Econometrics* 46: 185-200.
- Crespo-Cuaresma, J., Doppelhofer, G., and M. Feldkircher. 2014. The determinants of economic growth in European regions. *Regional Studies* 48 (1): 44-67.
- Cuadrado-Roura, J.R., Mancha-Navarro, T., and R. Garrido-Yserte. 2000. Regional productivity patterns in Europe: An alternative approach. *Annals of Regional Science* 34: 365-84.
- Daraio, C., and Simar, L. 2005. Introducing environmental variables in nonparametric frontier models: A probabilistic approach. *Journal of Productivity Analysis* 24 (1): 93-121.
- 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.
- Elhorst, J.P., 2009. Spatial panel data models. In: Fischer, M.M., Getis, A. (Eds.), *Handbook of Applied Spatial Analysis: Software Tools, Methods and Applications*. Springer-Verlag, Berlin.
- Elhorst, J.P. 2014. *Spatial econometrics: from cross-sectional data to spatial panels*. Springer, Heidelberg.
- Enflo, K., and P. Hjertstrand. 2006. Relative Sources of European Regional Productivity Convergence: A Bootstrap Frontier Approach. *Regional Studies* 43 (5): 643-659.
- Escribá J., and M.J. Murgui. 2014a. New estimates of capital stock for European regions (1995-2007). *Revista de Economía Aplicada* 66 (22): 113-137.
- Escribá J. and M.J. Murgui. 2014b. La base de datos BD-EURS (NACE Rev.1). *Investigaciones Regionales* 28: 173-194.
- Ezcurra, R., Pascual, P., and M. Rapún. 2007. Spatial Inequality in Productivity in European Union: Sectoral and Regional Factors. *International Regional Science Review* 30 (4): 384-407.
- Ezcurra, R., Irázoz, B., and M. Rapún. 2008. Regional inefficiency in the European Union. *European Planning Studies* 16 (8): 1121-1143.
- Ezcurra, R., and B. Irázoz. 2009. Spatial inequality in the European Union. *Economics Bulletin* 29 (4): 2648-2655.
- Färe R., Grosskopf S., Norris M., and Z. Zhang. 1994. Productivity growth, technical progress, and efficiency change in industrialized countries. *American Economic Review* 84: 66-83.
- Feng, G., and A. Serletis. 2009. Efficiency and productivity of the US banking industry, 1998-2005: evidence from Fourier cost functions satisfying global regularity conditions. *Journal of Applied Econometrics* 24:105-138.
- Fusco, E., and Vidoli, F. 2013. Spatial stochastic frontier models: controlling spatial global and

- local heterogeneity. *International Review of Applied Economics* 27 (5): 679-694.
- Gallant, A.R. 1981. On the bias in flexible functional forms and an essentially unbiased form – The Fourier flexible form. *Journal of Econometrics* 15: 211-245.
- Gallant, A.R. 1982. Unbiased determination of production technologies. *Journal of Econometrics* 20: 285-323.
- Gardiner, B., Martin, R. and P. Tyler. 2004. Competitiveness, productivity and economic growth across European regions. In: Martin, R., and P. Tyler (Eds.), *Regional Competitiveness*. Routledge, London and New York.
- Glass, A., Kenjegalieva, K., Paez-Farrell, J. 2013. Productivity growth decomposition using a spatial autoregressive frontier model. *Economics Letters* 119: 291–295.
- Glass, A.J., Kenjegalieva, K., and R.C. Sickles. 2014. Estimating efficiency spillovers with state level evidence for manufacturing in the US. *Economics Letters* 123 (2): 154–159.
- Glass, A.J., Kenjegalieva, K., and R.C. Sickles. 2016. A spatial autoregressive stochastic frontier model for panel data with asymmetric efficiency spillovers. *Journal of Econometrics* 190: 289–300.
- Greene, W.H. 2002. Fixed and random effects in stochastic frontier models. *Journal of Productivity Analysis* 23 (1): 7-32.
- Greene, W.H. 2005. Reconsidering heterogeneity in panel data estimators of the stochastic frontier model. *Journal of Productivity Analysis* 126 (2): 269-303.
- Greene, W.H. 2008. *The Econometric Approach to Efficiency Analysis*. In Fried, H.O., Lovell, C.A.K., and S.S. Shelton (Eds.), *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press, New York.
- Growiec, J. 2012. The world technology frontier: What can we learn from the US states? *Oxford Bulletin of Economics and Statistics* 74 (6): 777-807.
- Han, J., Ryu, D., and R.C. Sickles. 2016. Spillover effects of public capital stock using spatial frontier analyses: A first look at the data. In: Greene, W.H., Khalaf, L., Sickles, R.C., Veall, M., and M.C. Voia (Eds.), *Productivity and Efficiency Analysis*. Springer, Switzerland.
- Henderson, D.J., and R. Russell. Human capital and convergence: A production-frontier approach. *International Economic Review* 46 (4): 1167-1205.
- Henry M., Kneller R., and C. Milner. 2009. Trade, technology transfer and national efficiency in developing countries. *European Economic Review* 53:237–254.
- Hospers, G.J. 2002. Beyond the blue banana? Structural change in Europe’s geo-economy. In: *Proceedings of the 42nd Congress of the European Regional Science Association “From Industry to Advanced Services – Perspectives on European Metropolitan Regions”*. Available at ECONSTOR: <http://www.econstor.eu/handle/10419/115684>.
- Jondrow, J., Lovell C.A.K., Materov I.S., and P. Schmidt. 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. *Journal of Econometrics* 19 (2-3): 233-238.
- Kelejian, H.H., and I.R. Prucha. 1999. A Generalized Moments Estimator for the Autoregressive Parameter in a Spatial Model. *International Economic Review* 40: 509-533.
- Kneller R., and P.A. Stevens. 2003. The specification of the aggregate production function in the presence of inefficiency. *Economics Letters* 81:223–226.
- Kumar S. and Russell R. (2002) Technological change, technological catch-up, and capital deepening: relative contributions to growth and convergence, *American Economic Review* 92: 527–548.
- Kumbhakar, S.C. 1991. Estimation of technical inefficiency in panel data models with firm- and time-specific effects. *Economic Letters* 36:43–48.

- Kumbhakar, S.C., and C.A.K. Lovell. 2000. *Stochastic Frontier Analysis*. Cambridge University Press, Cambridge.
- Kumbhakar, S.C., and H.J. Wang. 2005. Estimation of growth convergence using a stochastic production frontier approach. *Economics Letters* 88: 300–305.
- López-Bazo, E., Vay á E., Mora, A.J., and J. Suri ñach. 1999. Regional economic dynamics and convergence in the European Union. *Annals of Regional Science* 33: 343-370.
- López-Bazo, E., Vay á E., and M. Art í. 2004. Regional externalities and growth: evidence from European regions. *Journal of Regional Science* 44 (1): 43-73.
- Mastromarco, C., Serlenga, L., and Y. Shin. 2013. Globalisation and technological convergence in EU. *Journal of Productivity Analysis* 40: 15–29.
- Mastromarco, C., Serlenga, L., and Y. Shin. 2013. Modelling technical efficiency in cross sectionally dependent stochastic frontier panels. *Journal of Applied Econometrics* 31: 281–297.
- Meeusen, W., and J. Van den Broeck. 1977. Efficiency estimation from Cobb-Douglas production function with composed errors. *International Economic Review* 18 (2): 435-444.
- Parente, S., and Prescott E.C. 2005. A unified theory of the evolution of international income levels. In: Aghion, P., and S. Durlauf (Eds.), *Handbook of Economic Growth*. Elsevier, Amsterdam.
- Pavlyuk, D. 2011. Application of the spatial stochastic frontier model for analysis of a regional tourism sector. *Transport and Telecommunication* 12 (2): 28–38.
- Pavlyuk, D. 2012. Maximum likelihood estimator for spatial stochastic frontier models. In: *Proceedings of the 12th International Conference “Reliability and Statistics in Transportation and Communication - 2012”*. Available at MPRA: <https://mpra.ub.uni-muenchen.de/43390/>.
- Pavlyuk, D. 2013. Distinguishing between spatial heterogeneity and inefficiency: Spatial stochastic frontier analysis of European airports. *Transport and Telecommunication* 14 (1): 29–38.
- Piribauer, P. 2016. Heterogeneity in spatial growth clusters. *Empirical Economics*. Available at Springer Link: <https://doi.org/10.1007/s00181-015-1023-y>.
- Ramajo, J., Márquez M.A., and J.M. Cordero. 2015. European regional efficiency and geographical externalities: A spatial nonparametric frontier analysis. In: *Proceedings of the International Conference on Regional Science “Innovation and Geographical Spillovers: New Approaches and Evidence”*. Available at SSRN: <http://ssrn.com/abstract=2729134>.
- Schmidt, A.M., Moreira A.R.B., Helfand, S.M., and T.C.O Fonseca. 2009. Spatial stochastic frontier models: accounting for unobserved local determinants of inefficiency. *Journal of Productivity Analysis* 31: 101-112.
- Schmidt, P., and R.C. Sickles. 1984. Production Frontiers and Panel Data. *Journal of Business and Economic Statistics* 2: 367-374.
- Silverman, B.W. 1981. Using kernel density to investigate Multimodality. *Journal of the Royal Statistical Society B* 43: 97–99.
- Theil, H. 1967. *Economics and Information Theory*. North-Holland, Amsterdam.

TABLE 1: Estimation results of spatial stochastic frontiers $y_{it} = \alpha_0 + \rho \mathbf{w}'_i \mathbf{y} + \mathbf{x}'_{it} \boldsymbol{\beta} + \varepsilon_{it}$ for EU-9 regions over 1995-2007

Inefficiency specification → Parameter ↓	Case 1 Time-invariant inefficiency $\varepsilon_{it} = v_{it} - u_i$ $v_{it} \sim N(0, \sigma_v^2)$ $u_i \sim N^+(\mu, \sigma_u^2)$	Case 2 Time-varying inefficiency $\varepsilon_{it} = v_{it} - u_{it}$ $v_{it} \sim N(0, \sigma_v^2)$ $u_{it} = h(t)u_i$ $h(t) = \exp(-\eta(t - T))$ $u_i \sim N^+(\mu, \sigma_u^2)$
<i>Production equation</i>		
α_0	2.021 ^{***} (3.93)	2.479 ^{***} (4.10)
ρ	0.293 ^{***} (5.17)	0.352 ^{***} (6.09)
β_1	-0.844 ^{***} (-5.84)	-1.036 ^{***} (-7.37)
β_2	1.939 ^{***} (13.32)	1.936 ^{***} (13.31)
β_3	0.126 ^{***} (9.35)	0.139 ^{***} (10.67)
β_4	0.097 ^{***} (5.17)	0.109 ^{***} (5.89)
β_5	-0.241 ^{***} (-8.35)	-0.254 ^{***} (-8.77)
δ_1	-0.006 ^{***} (-3.67)	-0.011 ^{***} (-6.28)
δ_2	0.0002 ^{***} (3.75)	0.0002 ^{***} (4.39)
<i>Inefficiency equation</i>		
σ_v^2	0.0006 ^{***} (25.85)	0.0006 ^{***} (26.30)
η	-	0.008 ^{***} (7.70)
μ	0.440 ^{***} (9.18)	0.379 ^{***} (14.34)
σ_u^2	0.032 ^{***} (5.39)	0.030 ^{***} (5.45)
Log-likelihood	3156.324	3185.031

NOTE: z-ratios are shown in parentheses. Significance: ***=1% level; **=5% level; *=10% level.

TABLE 2: Summary statistics for estimated EU-9 regional technical efficiency (time-varying inefficiency production frontier model)

	Mean	Median	Std. Dev.	Obs.
EU-9 1995-2007	0.677	0.678	0.113	1560
<i>Over space</i>				
AT	0.621	0.614	0.090	117
BE	0.750	0.739	0.109	143
DE	0.615	0.636	0.148	208
ES	0.698	0.671	0.090	208
FR	0.679	0.685	0.070	286
IT	0.705	0.698	0.126	273
NL	0.688	0.702	0.112	156
PT	0.588	0.567	0.073	65
SE	0.688	0.680	0.054	104
<i>Over time</i>				
1995	0.665	0.668	0.116	120
1996	0.667	0.670	0.116	120
1997	0.669	0.672	0.115	120
1998	0.671	0.674	0.115	120
1999	0.673	0.676	0.114	120
2000	0.675	0.678	0.114	120
2001	0.677	0.680	0.113	120
2002	0.679	0.682	0.113	120
2003	0.681	0.684	0.112	120
2004	0.683	0.686	0.111	120
2005	0.685	0.690	0.111	120
2006	0.687	0.690	0.114	120
2007	0.689	0.692	0.110	120

FIGURE 1. The stochastic frontier production function

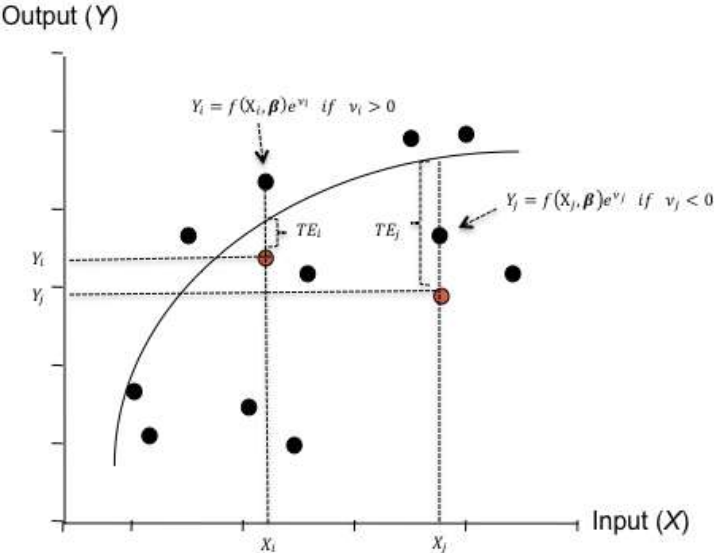


FIGURE 2. European NUTS-2 regions considered in the empirical analysis



FIGURE 3. Quantile maps of productivity in the EU-9 in 1995 and 2007, and associated Moran's scatterplots (Dark-shaded regions: more productive; Light-shaded regions: less productive)

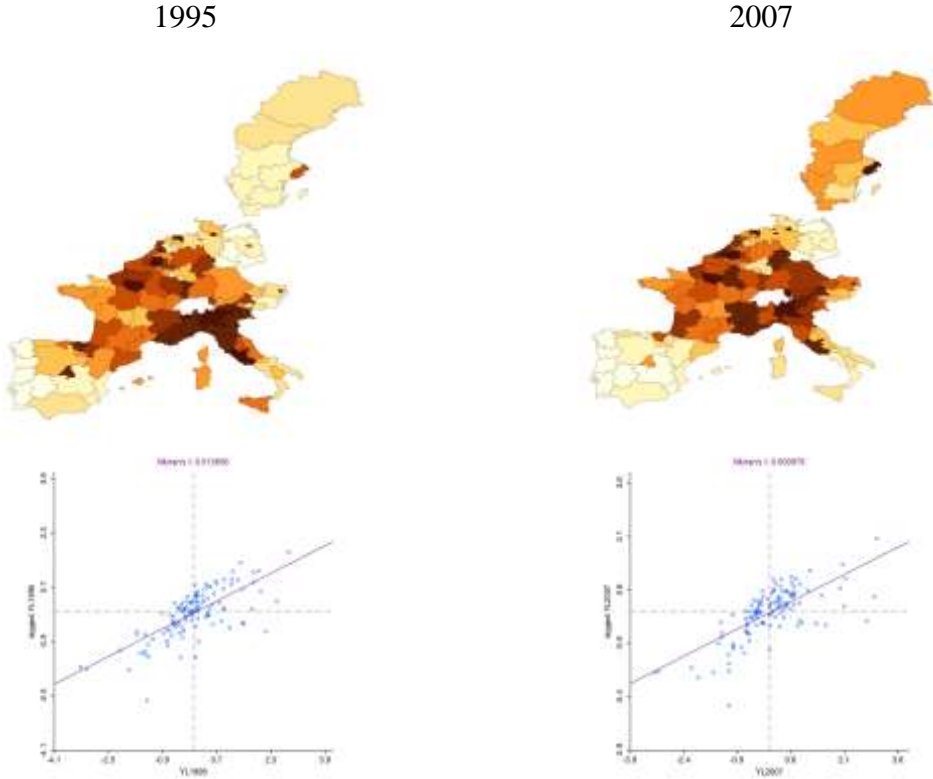


FIGURE 4. Regional convergence and inequality in productivity in the EU-9: unconditional β -convergence (first panel) and Theil index -1995=100- (second panel)

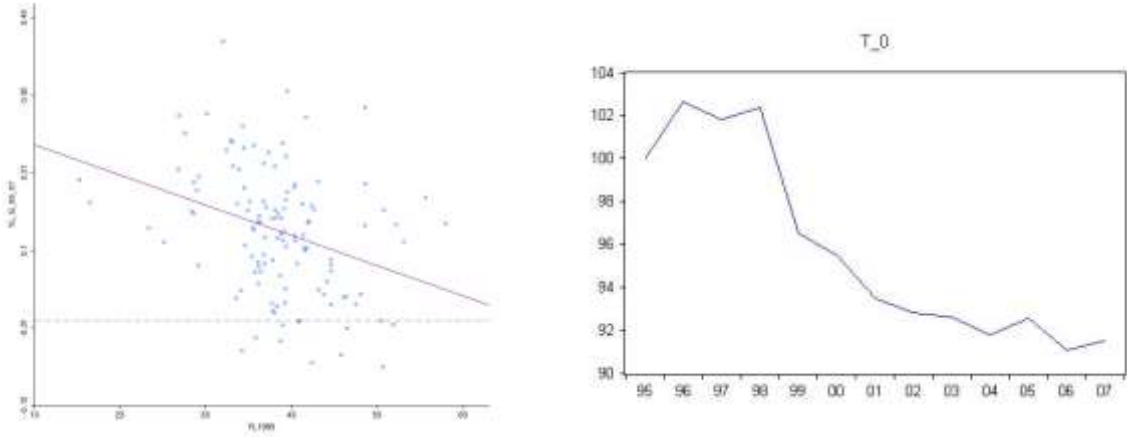


FIGURE 5. Kernel density of the technical efficiencies (Full sample: EU-9 1995-2007)

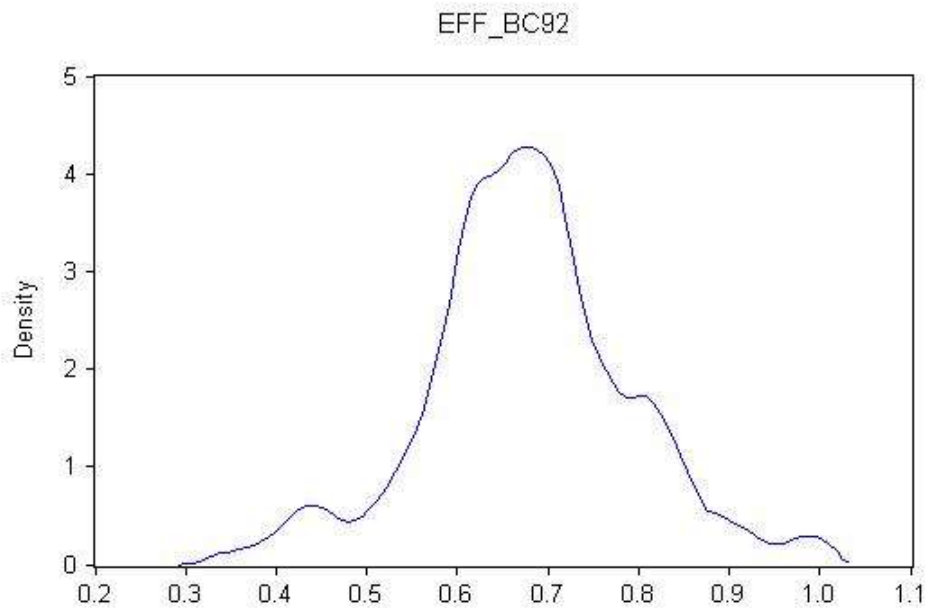


FIGURE 6. EU-9 regional efficiency scores: time-series pattern (yearly mean, median, 0.25 and 0.75 quantile scores)

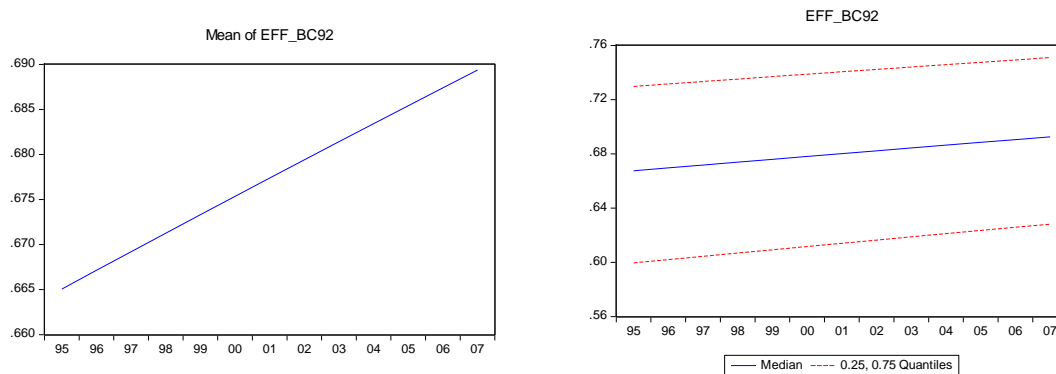


FIGURE 7. EU-9 mean regional efficiency scores: cross-section pattern

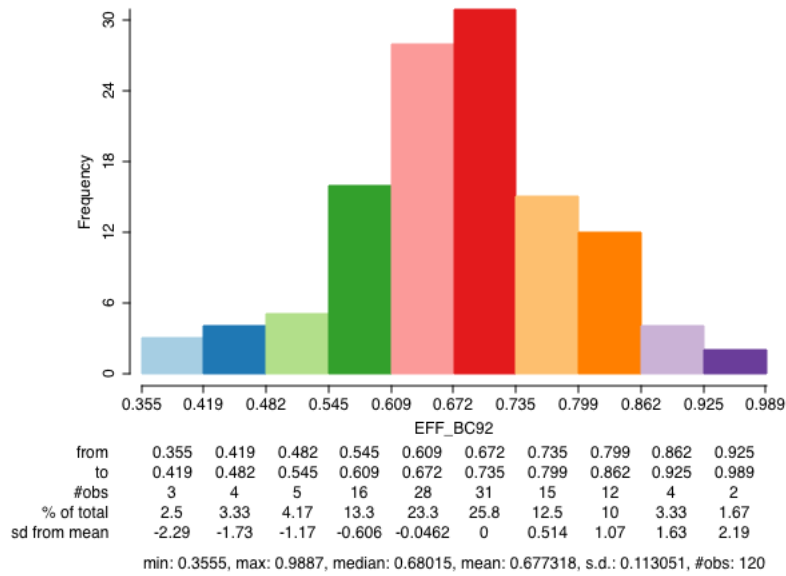
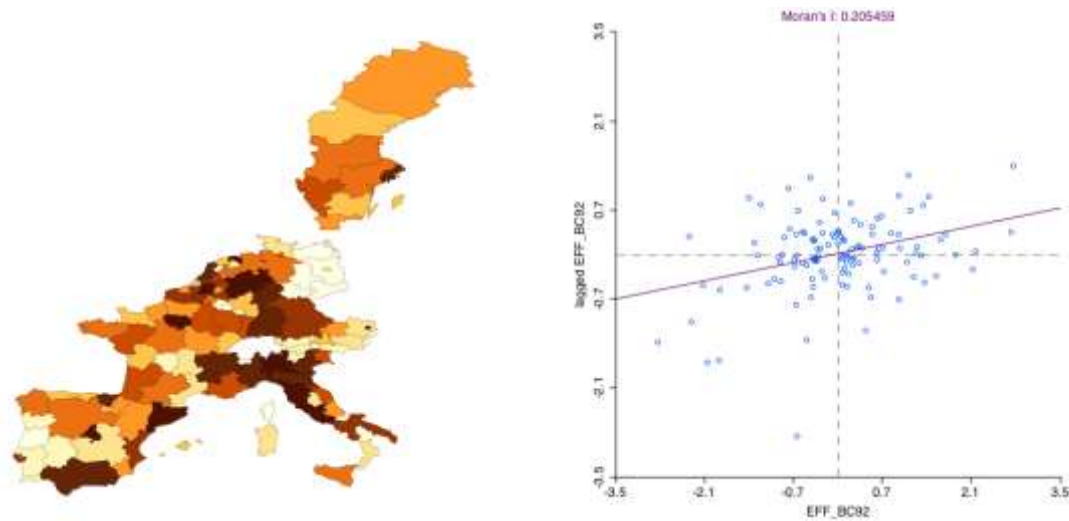


FIGURE 8. Quantile map of EU-9 mean regional efficiency scores, and associated Moran's scatterplot (Dark-shaded regions: more efficient; Light-shaded regions: less efficient)



NOTE: Light brown color → [0.36,0.54], Dark brown color → [0.83,0.99]

FIGURE 9. LISA maps of EU-9 mean regional efficiency scores

Cluster map

Significance map



NOTE: Red color→High-High, Dark blue color→Low-Low; Dark green color→ p -value=0.01, Light green color→ p -value=0.05; White→Not significant.

FIGURE 10. Labor productivity growth [y-axis] versus efficiency changes [x-axis], 1995-2007

