Towards more effective structural funding – regional efficiency in using infrastructure and human capital

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1 Introduction

According the Council Regulation (EC) No 1083/2006 regions eligible for funding from the EU Structural Funds under the Convergence objective between 2007 and 2013 enclose all regions, whose gross regional product (GRP) per capita was less than 75% of the average GRP per capita of the EU-25 between 2000 to 2002.

Choosing GRP per capita (based on purchasing power parities) as a yardstick has several implications for the allocation of funds. On the one hand, regions that benefit the most are, per definition, among the poorest regions in Europe. Thus the orientation towards GRP is arguably in line with EU's social objective of regional cohesion. On the other hand, the indicator is limited, if the focus is on the regions' comparative structural disadvantage. As a consequence Athanassopoulos (1996) proposes to allocate public funds according the regions' efficiency rather than per-capita-income.

The presented paper follows this idea and intends to identify a more appropriate funding scheme by taking into account both, the level of per capita income and the degree of efficiency. In so doing, the paper is structured as follows.

The first step foresees to identify total (output-) efficiency of EU regions at NUTS 2 level in section 2. For this purpose, we apply an outlier robust enhancement of the data envelopment analysis (DEA), the so-called order-α-frontier analysis (Daouia and Simar 2005, Daraio and Simar 2006). The analysis yields a picture similar to the regional distribution of per-capita-income characterized by a clear East-West divide.

The existence of a spatial factor conflicts with a basic assumption of DEA, which indeed presumes a strong degree of independency of the operating units. Therefore, section 3 introduces a geoadditive regression analysis based on markov fields, which allows for decomposing the total efficiency into a smoothed spatial and a non-spatial effect. The non-spatial effect gives an idea on a region's efficiency compared to the neighboring and nearby regions and can be interpreted as structural efficiency (Schaffer et al. 2009).

In order to identify a more effective funding scheme, the concluding section aims to account for both, the regions' efficiency and per-capita income. Relatively poor and inefficient regions are considered structurally disadvantaged and therefore particularly eligible for direct investments (e.g. to promote small and medium sized enterprises). In contrast, public infrastructure might indeed alleviate bottlenecks in the case of relatively poor and efficient regions. Thus, investments in modern transport and communication networks are particularly promising in this case.

2 Identification of regional efficiency

Regional efficiency analysis traces back to several studies on the economic performance of Asian regions. Macmillan (1986) and Hashimoto and Ishikawa (1993) applied DEA to rate the efficiency of Chinese and Japanese cities respectively. Charnes et al. (1989) used the same methodology to identify urban industrial performance and assess regional planning tools in China, and Seifert and Zhu (1998) applied DEA to monitor the productivity growth of China's industries over several decades.

More recently regional DEA has been applied to analyze regional efficiency against the background of EU regional policy (Karkazis and Thanassoulis 1998, Castells and Solé-Ollé 2005). This is particularly interesting, as the efficiency argument opens the door for two mutually exclusive investment decisions. A government's objective function could, on the one hand, include the goal to maximize the productivity of funds. Consequentially, investments into rather efficient mostly structurally advanced regions would promise the highest returns (Berhman and Craig 1987). On the other hand, policy makers might aim to minimize the regional disparities. In this case funds should particularly be warranted to less efficient structurally disadvantaged regions (Athanassopoulos 1996).

Considering EU policy, the disparity argument clearly outweighs the productivity one. Council Regulation (EC) No 1083/2006, for example, rules that the identification of eligible regions is determined by the regional disparity. However, according to the regulation, regional disparity is rather reflected by the per-capita-income level and not by the regions' efficiency. In fact, regions eligible for structural funds under the convergence objective must show per-capita-income of less than 75% compared to the EU average.

The strong focus on the per-capita-income has profound implications for the assessment of regional disparities and the provision of funds. In particular, the approach might turn out to be a comparatively expansive way to reach the political objective of regional cohesion compared to an allocation of funds based on the regions' income level and degree of efficiency.

The presented paper proposes such a mixed strategy and therefore identifies, in a first step, the efficiency of EU regions.

2.1 Methodological remarks

The estimation of the regional efficiency follows the basic principles of DEA.[1] These comprise the selection of decision making units (DMUs), the definition of inputs and outputs and the formulation of the mathematical model.

Definition of DMUs

DMUs are characterized by a uniform production function to transfer a set of inputs into one or multiple outputs. Technological efficiency, for example, is often analyzed at the level of firms that produce the same goods or services. If the focus is on regional efficiency, DMUs are generally defined as spatial entities.

Following the territorial system of the European Union – the so-called Nomenclature Territorial Statistical Units (NUTS) – efficiency is analyzed at the NUTS 2 level, which can be considered the basic administrative unit chosen by the EU for a broad set of regional policies.

Definition of inputs and outputs

The regions' economic performance is strongly determined by the availability of immobile and polyvalent production factors (Biehl 1995). According to this idea, a certain level of human and infrastructure capital can be considered a necessary precondition for a favorable regional development (Barro and Sala-i-Martin 1991, Nijkamp 2000, Banister and Berechman 2001). Therefore, the chosen inputs aim to reflect these factors.

Human capital is defined as the percentage of a region's labor force that belongs to the human resources in science and technology (HRST). Following the Canberra Manual, HRST comprise all members of the labor force, who either dispose of tertiary education in the field of science and technology, or are employed in a corresponding occupation where the above qualifications are normally required (OECD 1993). In this context, the requirements are in line with internationally harmonized standards: the International Standard Classification of Education (ISCED) and the International Standard Classification of Occupation (ISCO).

With regard to the transport infrastructure, the regions' centrality or potential accessibility is taken into account. Presuming that a regions' attraction increases with size and declines with distance the applied indicator A accounts for the minimum travel time between the considered

[1] In the following we assume a basic familiarity with DEA. Among others, Charnes et al. (1994) or Cooper et al. (2006) provide a good introduction into DEA.

region i and any other European NUTS 2 region j by using road, rail or air.

$$(1) \qquad A_i = \sum_{j=1}^{m} pop_j \cdot e^{\omega \cdot \min(t_{rail}(i,j), t_{road}(i,j), t_{\text{air}}(\text{i,j}))} ,$$

where m denotes the number of the European NUTS 2 regions, *pop* the regions' population and t_{rail}, t_{road} and t_{air} the travel time between region i and j by rail, road and air respectively (Schoch 2004). Parameter ω is a weighting factor that fulfils the following condition:

$$(2) \qquad e^{\omega \mathrm{T}} = 0.5 \;\text{ for T=180 minutes.}$$

Thus, the population, which can be reached within 180 minutes, is weighted by 0.5.[2] Smaller weights are attributed to the population further away and higher weights account for the GRP that can be reached faster.

On the output side, the GRP per capita in purchasing power parity is considered. This allows for a comparison of the regions' per-capita income with the efficiency in generating this income.

Mathematical formulation

Traditional DEA can be considered one of the most popular tools to measure efficient production boundaries of firms or regions. However, the models are often found to be rather sensitive to outliers. The presented order-α-frontier analysis, which is described in full detail by Daouia and Simar (2003), aims to overcome this shortcoming by defining a frontier function that leaves out extreme observations. Presuming that regions improve their efficiency more likely by growing outputs rather than decreasing inputs, the output-oriented version of the model is applied for this study.

We start with a brief specification of the traditional DEA model (Equations (3) to (5)), which defines the baseline for the extension according equations (6) and (7).

Any region disposes of a set of inputs $x \in \mathrm{R}_+^p$ to generate a set of outputs $y \in \mathrm{R}_+^q$. Feasible combinations of (x,y) are defined as:

$$(3) \qquad \Psi = \left\{ (x,y) \in R_+^{p+q} \,\middle|\, x \text{ can produce } y \right\}.$$

The frontiers of Ψ reflect maximum outputs that can be produced with given inputs. Thus, the regions' efficient frontier can be defined in the following way:

2 The half-value period has been set to 180 minutes fort wo reasons. First, three hours are often cited as acceptable travel time for daily business trips and used for calibration of passenger transport models (e.g. Schoch 2004). Second, the analyses with parameters that correspond to a half-value period of 120 and 90 minutes respectively hardly affected the efficiency results.

(4) $$Y^{\partial}(x) = \left\{(x, y^{\partial}(x)) \middle| y^{\partial}(x) \in Y(x) : \lambda y^{\partial}(x) \notin Y(x),\ \forall \lambda > 1\right\}$$

where $Y(x)$ describes the set of technologically feasible outputs, and $y^{\partial}(x)$ denotes the maximum achievable output of a unit that produces at input level x. This, in turn, allows the definition of a unit's efficiency score as:

(5) $$\lambda(x,y) = \sup\left\{\lambda \middle| (x, \lambda y) \in \Psi\right\} = \sup\left\{\lambda \middle| \lambda y \in Y(x)\right\}$$

where $\lambda(x,y) \geq 1$ is the proportionate increase of output y a region operating at input level x has to attain to be efficient.

The frontiers of Ψ, which are unknown in practice, can be determined by nonparametric estimators, such as the free disposal hull (FDH) estimator (Deprins et al. 1984). However, these estimators often envelop all data points, which in turn makes traditional DEA rather sensitive for outliers.

The problem can be solved by using more robust estimators which deal with extreme observations in a different way. Instead of defining the efficient boundary according the uppermost technically achievable output (for any given input), extreme observations can for example be allowed to lie above a partial frontier (Cazals et al. 2002). For this case, Aragon et al. (2005) introduced the concept of the order-α partial frontier ($\alpha \in [0,1]$) which is applied for the presented study.

With $S_{Y|X}(y \mid x)$ defined as the probability $\text{Prob}(Y \geq y \mid X \leq x)$ and $F_X(x)$ as the probability $\text{Prob}(X \leq x)$, Daouia and Simar (2003) define the order-α-quantile output efficiency score for each unit $(x,y) \in \Psi$ as:

(6) $$\lambda_{\alpha}(x,y) = \sup\left\{\lambda \middle| S_{Y|X}(\lambda y \mid x) > 1 - \alpha\right\} \text{ for } F_X(x) > 0 \text{ for } \alpha \in [0,1]$$ [3]

Note that, following this approach, each unit is only compared with units disposing of equal or worse input levels. A unit (x,y) is efficient at level α, if it lies on the calculated frontier, this means if $\lambda_{\alpha}(x,y) = 1$. In this case, the unit is dominated by a unit with lower input with a probability $\leq$ 1-α.[4] Units below the efficient boundary ($\lambda_{\alpha}(x,y) > 1$) are considered inefficient. This means a unit with similar or worse input delivers higher output with a probability > 1-α. On the contrary, units above the frontier ($\lambda_{\alpha}(x,y) < 1$) could reduce their outputs but would remain output efficient.

The applied nonparametric estimator of $\lambda_{\alpha}(x,y)$ is obtained by substituting $S_{Y|X}(y \mid x)$ with its

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[3] The efficiency score converges from below to the Debreu-Farell output efficiency measure $\lambda(x,y)$.

[4] In case a unit's input equals the minimum level, which means $F_X(x) = 0$, the unit cannot be dominated by a unit with less input and is therefore considered to be efficient ($\lambda_{\alpha}(x,y) = 1$).

empirical correspondent $\bar{S}_{Y|X,n}(y \mid x)$, based on the samples (X_1,Y_1), …, (X_n,Y_n) where X is the observed input and Y the output. This results in the empirical efficiency score $\bar{\lambda}_{\alpha,n}(x,y)$.

(7) $$\bar{\lambda}_{\alpha,n}(x,y) = \sup\left\{\lambda \middle| \bar{S}_{Y|X,n}(\lambda y \mid x) > 1-\alpha\right\}$$

The order-α-frontier analysis is particularly charming for samples with extreme observations as they easily might occur for a sample of regions. Furthermore the approach accounts to some extent for the heterogeneity of the sample, as each region is only compared with regions whose input levels are equal or worse.

2.2 Results

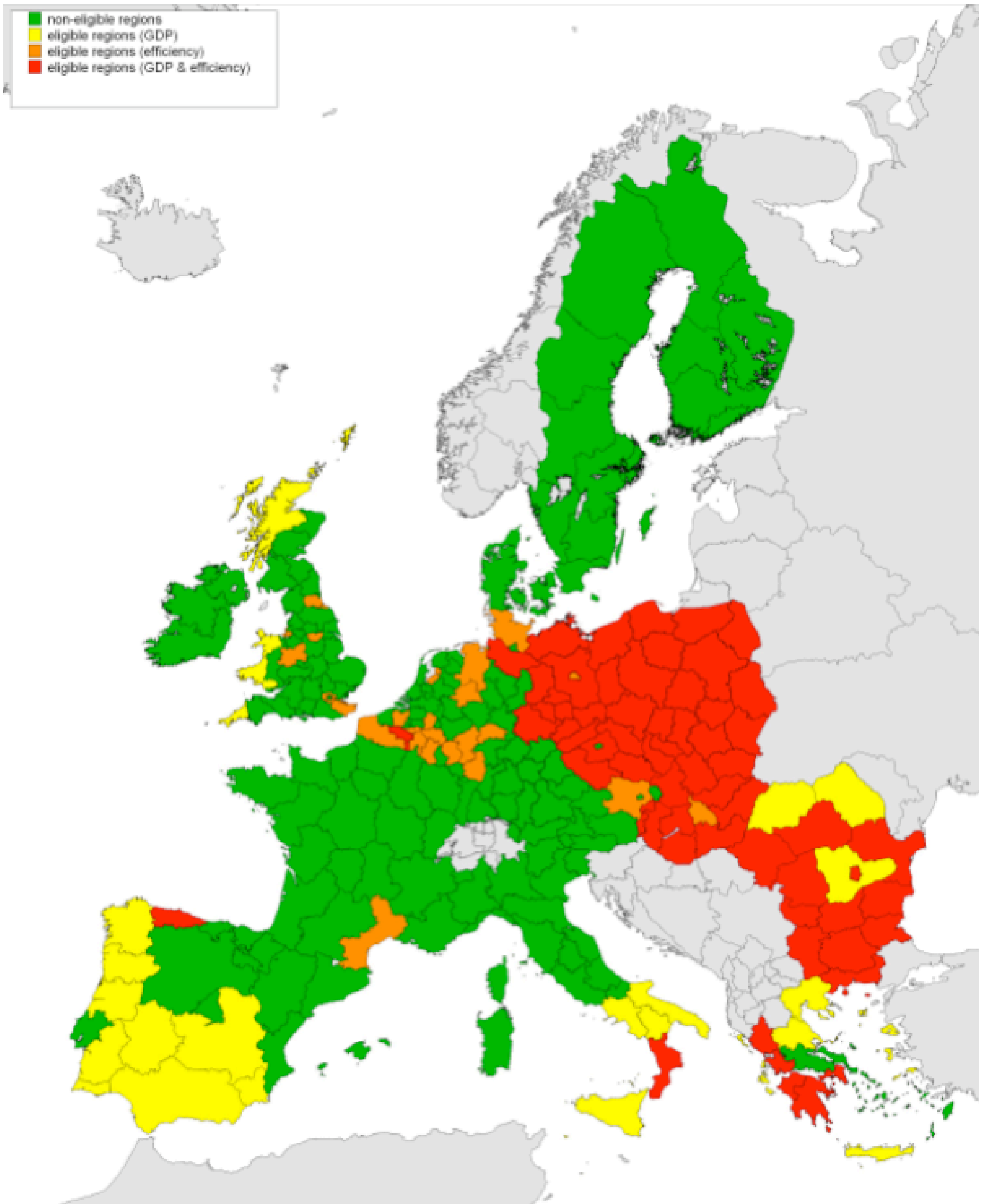
The results, illustrated by figure 1, derive from the application of the order-α-frontier analysis for α = 0.05. A region is considered comparatively inefficient in using its infrastructure and human capital, if one or more other regions equipped with a similar or worse level of human and infrastructure capital generate(s) higher levels of output.

The respective orange- and red-shaded regions can be considered comparatively disadvantaged with regard to their structure and/or location in space. If the criteria of eligibility would follow efficiency rather than per-capita-income, these regions would qualify. On the contrary, the yellow- and green-shaded regions show the highest level of efficiency, as they deliver comparatively high per-capita-income with the given inputs. Return on public investments might be relatively high in this case. At the same time the funding of these regions would, most likely, conflict with the cohesion objectives of EU regional policy.

In total, the efficiency analysis is based on 257 NUTS 2 regions.[5] Based on the per-capita-income, slightly more than one third of these regions (92) qualify for funding from Structural Funds under the Convergence objective (EC 2007). A total of 67 out of these 92 regions (73%) would still qualify for financial aid, if the criteria would be (low) efficiency rather than (low) income (red-shaded regions). As a consequence, 25 in the majority East-European regions that receive financial aid under the current criteria would lose their eligibility (yellow-shaded regions). Instead 25 more inefficient and in the majority West-European regions would qualify for receiving Structural Funds (orange-shaded regions) – provided that the total number of eligible regions remains constant.

[5] While Bulgarian and Romanian regions are included, oversea departments and the regions of Cyprus and Malta remain unconsidered.

Figure 1. Efficiency of European NUTS 2 regions, order-a-frontier analysis, 2002???



Source: Own calculations

Despite the slight shift of potential eligibility towards the West, the findings on efficiency reveal a pattern rather similar to the picture that could be found with regard to the regions' income. While most Eastern regions can be classified relatively inefficient, Western European regions turn out to be comparatively efficient. This, in turn, yields the question, whether the DMUs' activities are indeed independent, as presumed in the DEA model. In order to answer this question, regional efficiency is decomposed into a spatial and a non-spatial effect in the next step. For this purpose, the paper follows a geoadditive regression analysis, which is introduced in section 3. The results provide valuable insights for increasing the effectiveness of Structural Funds (further discussed in the concluding section 4), no matter if eligibility is defined according the level of income or the degree of efficiency.

3 Decomposition of regional efficiency

3.1 Methodological remarks

DEA models generally imply independent production activities of the considered DMUs. While this assumption often holds for the frontier analysis at firm level, it is questionable if the model aims to estimate efficiency of regions. In contrast, efficiency could indeed be affected by neighborhood relations in this case. The presented study takes this possibility into account and, as a consequence, aims to isolate spatial and structural efficiency.

The decomposition is based on a geoadditve regression analysis, which allows for considering the spatial distribution of a given variable. Thus, the approach presumes that the regions' efficiency relies, on the one hand, on the intraregional setting – the non-spatial arguably structural efficiency - and, on the other hand, on the efficiency of nearby regions – the spatial efficiency.

The basic principle of the approach foresees to smooth the observed data, which yields decreasing deviations of the variables assigned to neighboring units. The difference between observed and smoothed data than identifies the non-spatial factor driven by the units' structure rather than their location in space. [6]

The model set up starts with the definition of neighborhood. While distance between points might serve as a good indicator for neighborhood in the continuous case, the indicator is more problematic for analyzing regions, where localization is discrete (Brezger 2004). Instead, two regions r and s are defined as neighbors $r \sim s$, if they share a border. The smoothing algorithm, which is weighted by the length of the common border (ω_{rs}), presupposes a growing regional interdependence with increasing length of ω_{rs}.

The mathematical formulation of the model follows the principles of structured additive regression analysis and therefore aims at substituting a usual parametric by a flexible nonparametric parameter, containing in this case spatial information (Fahrmeir et al. 2001, Hastie and Tibshirani 1990). Since the presented study concentrates on the spatial distribution of the efficiency as the response variable, no parametric covariables are considered. Therefore, the nonparametric regression model can be defined as (Fahrmeir and Lang 2001):

(8) $$\overline{\lambda}_{\alpha,n}(x_i, y_i) = f_{geo(i)} + f_{rand(i)}$$

[6] A more detailed introduction into the field of geoadditive regression analysis is given by Fahrmeir et al. (2007).

where $\bar{\lambda}_{\alpha,n}(x_i,y_i)$ is the empirical efficiency score of region i (defined by equation (7)) and $f_{geo(i)}$ the spatially smoothed factor of region $i = 1,...,n$. The remaining term $f_{rand(i)}$, generally considered the normally distributed error e_i, is interpreted as structural factor that cannot be explained by the spatial correlation.[7]

In order to smooth the regions' spatial factor a penalizing term, based on the least square method (PLS), is introduced in equation (9). In this preliminary step, the weights ω_{rs} remain unconsidered.

$$(9) \qquad PLS(\mu) = \sum_{i=1}^{n}(y_i - f_{geo(s_i)})^2 + \mu \sum_{s=2}^{d} \sum_{r \in N(s), r<s} (f_{geo(r)} - f_{geo(s)})^2$$

where *N(s)* is the set of neighbors surrounding region *s* and μ is a parameter to control the smoothing intensity. The first term sums up the squared differences of observed data and modeled spatial factor. The smoothing process, defined in the second term, multiplies μ with the cumulated squared differences of spatial factors for all neighborhood relations.

In line with Fahrmeir et al. (2007) the penalizing approach, which includes the minimization of *PLS(μ)*, can be interpreted in Bayesian way. This, in turn, yields markov random fields. As a consequence, the application of the model follows a Bayesian approach (with fully Bayesian inference) and is simulated by markov-chain-monte-carlo (MCMC) technique.[8]

In a last step, the expected value γ of the nonparametric spatial factor $f_{geo(i)}$ is defined as the average of the expected values of neighboring regions. Given the distribution of γ_r for all neighbors and introducing the weights ω_{rs} the conditional distribution of the expected spatial factor of region *s* (γ_s) is defined normally distributed as:

$$(8) \qquad \gamma_s | \gamma_r \sim N\left(\frac{\omega_{sr}}{\omega_{s+}} \sum_{r \in \delta_s} \gamma_r, \frac{\tau^2}{\omega_{s+}}\right)$$

where δ_s is the set of neighbors of region *s* and ω_{sr} the weight of neighbor *r*. ω_{s+} denotes the cumulated weights of all regions neighboring *s*. The variance parameter τ^2 controls the level of variation between the model result and the expected value.[9]

The remaining non-spatial factor is considered normally distributed as well and can be defined as $f_{rand(s_i)} \sim N(0,\tau^2)$.

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7 Presuming that the observed data are correct, we consider the remaining error as irrelevant.

8 For this purpose the software BayesX has been applied. The algorithm and its computation is decribed in detail by Brezger et al. (2009).

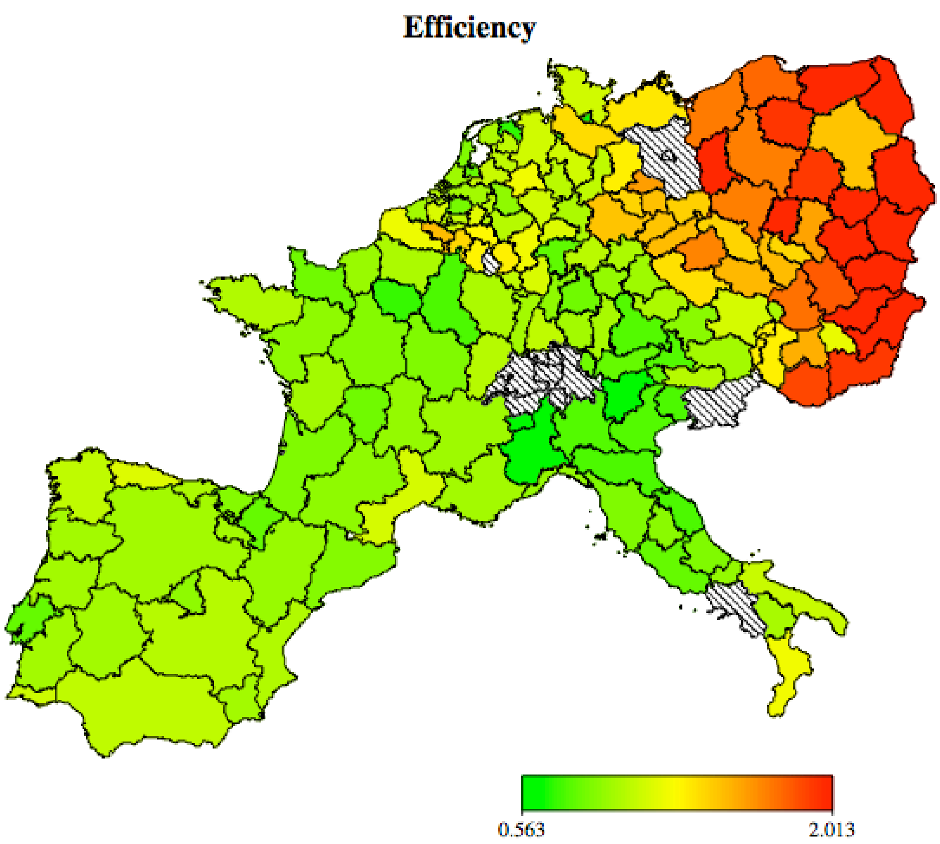
9 Note that the model behind equation (8) is equivalent to the penalizing model defined by equation (7) (see Fahrmeir et al. 2007, p. 390)

Based on the conditional expectation $\gamma_s|\gamma_r$ defined by equation (8), the MCMC-simulation results in a common distribution for the vector $\gamma = (\gamma_1, \gamma_2, ..., \gamma_n)$. Thus, the estimated spatial factor can be identified for all regions in the last step.

3.2 Results

For technical reasons the analysis is limited to the core of continental Europe. This is partly due to the definition of common borders, which makes it difficult to interprete results of islands, and partly due to a lack of data.[10] Therefore, efficiency scores are recalculated for the new limited sample of regions. Low scores point to a comparatively high efficiency and vice versa. As shown by figure 2, the sample is again characterized by a clear spatial pattern.

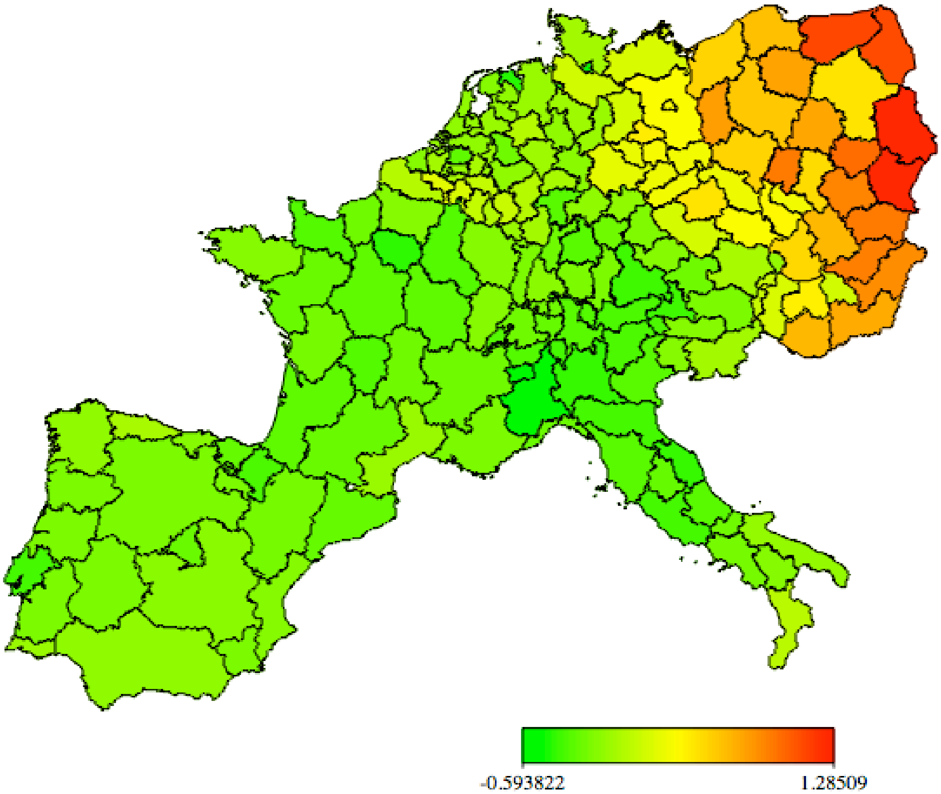
Figure 2. Efficiency scores of selected regions, order-a-frontier analysis, 2002



The findings of the geoadditive regression analysis confirm the strong spatial interdependency and identify, five years after the EU enlargement in 2004, a clear East-West divide. The smoothed spatial effect is given by figure 3.

[10] Missing data for the Baltic States result in the exclusion of Finland and Sweden.

Figure 3. Efficiency of selected regions, smoothed spatial factor, 2002



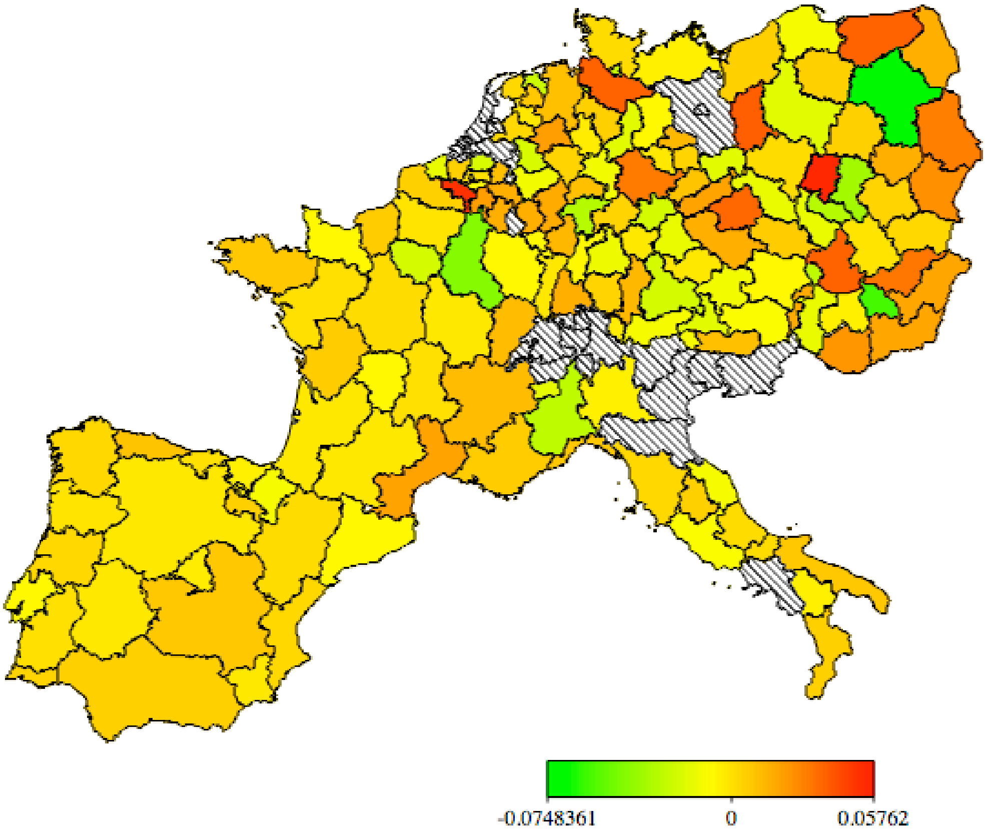
Green-shaded regions can, due to their well-performing neighbors, be expected to use their inputs in a comparatively efficient way. By contrast, red-shaded regions are surrounded by comparatively inefficient regions which, in turn, yields to rather low expectations in terms of efficiency.[11]

Besides the spatial factor, the regions' efficiency is also driven by a non-spatial intraregional effect. This effect, illustrated by figure 4, can be interpreted as structural effect.

According figure 4, a red-shaded region k is considered comparatively inefficient, if regions *in the greater neighboring area of region k* equipped with a similar or worse level of human and infrastructure capital generate(s) higher levels of per-capita-income. By contrast, a green-shaded region is efficient compared to its nearby regions.

[11] Based on the performance of the surrounding regions, the algorithm estimates the spatial efficiency for all regions of the sample.

Figure 4. Efficiency of European NUTS 2 regions, non-spatial structural factor, 2002???



Compared to figure 2 and 3, the East-West divide almost vanishes in figure 3. Instead structural efficiency of Eastern regions can be relatively high, if the region's performance is well above the expected results.

4 Conclusions - towards more effective funding schemes

Taking into account the regions' absolute income level and their structural efficiency, four regional types can be identified: rich and efficient, rich and inefficient, poor and efficient and finally poor and inefficient.

A policy devoted to the efficiency argument would aim to maximize return on public investments and would indeed prefer financial aid for the efficient regions. If, however, the focus is on the equity argument, two alternative strategies arise. First, the distribution of financial aid could be based on the degree of efficiency, which in turn yields to a funding of the relatively inefficient structurally disadvantaged regions (Athanassopoulos 1996, Camagni 1990). In so doing, eligible regions would be more spread across the EU and more regions in Western Europe would benefit from the Structural Funds.

Second, and in line with the factual EU regional policy, funds could be provided to the relatively poor regions. Nevertheless the effectiveness of funding could still be increased in this case, if the regions' structural efficiency would be taken into account as well.
This is due to the fact that the Structural Funds, particularly the European Regional Development Fund (ERDF), aim to increase eligible regions' competitiveness in a direct and indirect way: Directly productive funds include job-creating investment mainly assigned to business. Indirectly productive investments foresee, among others, the creation of new transport and communication infrastructure.
Structurally inefficient (and poor) regions' ability to attract private capital and subsequently to generate income is too low relative to the available human capital and public infrastructure. Thus, the potential stimulation of the economy induced by the additional provision of public goods is probably modest in nature. As a consequence, regional funding should focus on structural inputs in the form of direct investments to strengthen small and medium sized enterprises and to encourage the foundation of new companies.
On the contrary, poor but structurally efficient regions are comparatively more successful in the attraction of private capital. Thus, the provision of public goods, namely modern infrastructure and improved institutional education, might easily turn out to be more effective compared to direct investments initiated by regional policy-makers.

It can be concluded that a differentiation of financial aid into direct job creating investments and the enhanced provision of public goods could increase the overall productivity of regional funds. However, the preference for a more precise funding, based on the regions' efficiency, should not be seen as an advocate for exclusive investments of one or the other form. It rather supports the idea of a more region-specific financial aid while still having in mind the complementarity of different kinds of structural funds.

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