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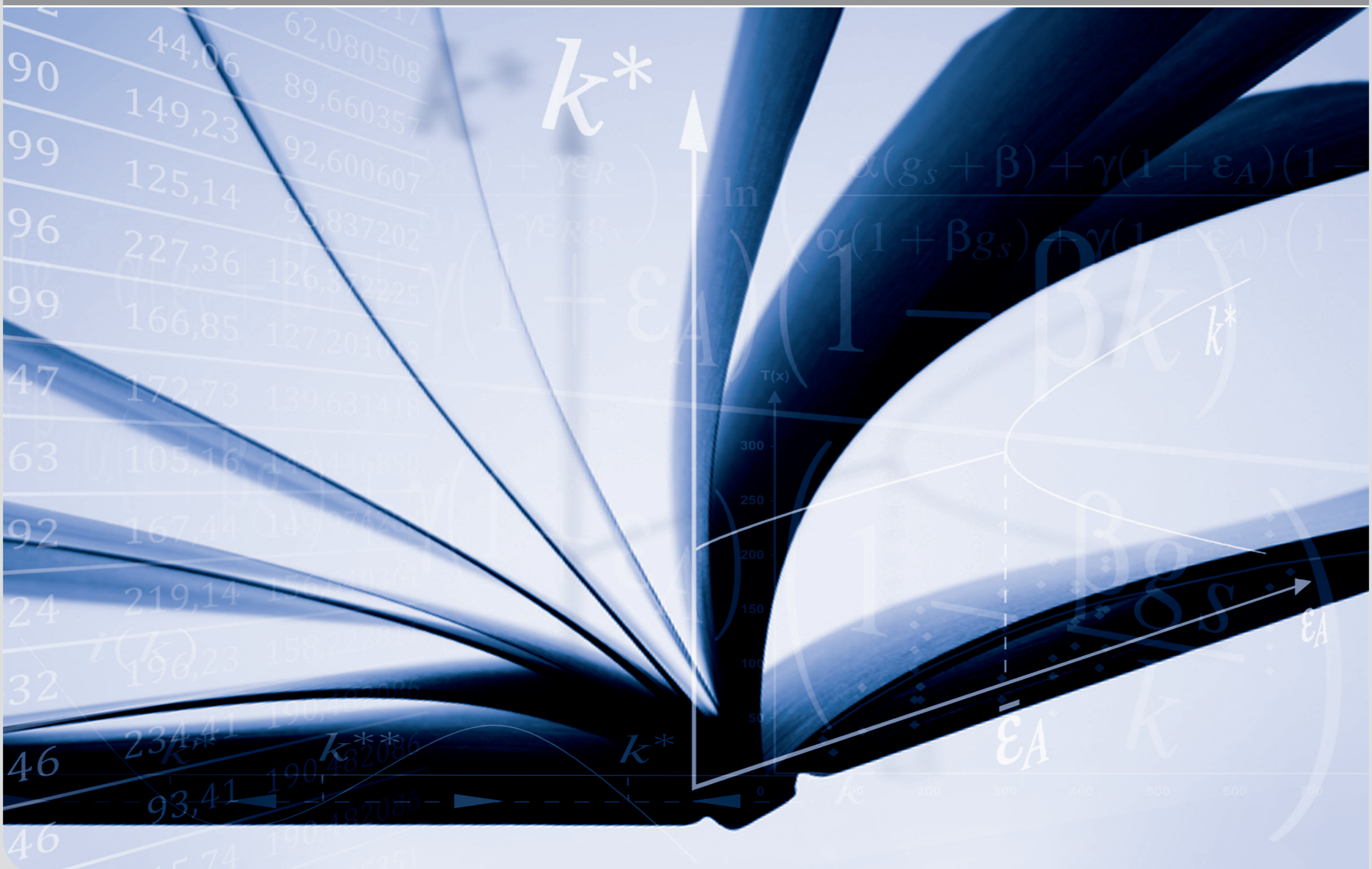

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DECOMPOSING REGIONAL EFFICIENCY

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Abstract : Applying an outlier robust extension of the data envelopment analysis (DEA) followed by a geoadditive regression analysis, this study identifies and decomposes the efficiency of 439 German regions in using infrastructure and human capital. The findings show that the regions' efficiency is driven by a spatial and a non-spatial, arguably structural factor. As a consequence, concrete regional funding schemes, shaped by best practice results, might not be appropriate for all regions. Instead, a more differentiated funding scheme that accounts for both spatial and structural factors seems more promising.

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DECOMPOSING REGIONAL EFFICIENCY

1. INTRODUCTION

If Germany is analyzed at regional level, a clear East-West divide in terms of per-capita income and labor productivity can be found. Twenty years after unification, income and productivity are generally still significantly lower in East German regions (Federal Statistical Office 2009). As a consequence, national and European funds have been used extensively to enhance the level of region-specific production factors such as transport infrastructure and human capital.

There is a broad consensus among regional scientists that the availability of human capital and modern transport infrastructure defines, among other factors, a necessary (but generally not sufficient) requirement for regional growth.[1] At the same time, the presence of these factors is of little help if they are not used effectively.

This paper follows this line of thought and identifies the efficiency of 439 German regions in their use of infrastructure and human capital. For this purpose, the so-called order-α frontier analysis is applied (Daouia and Simar, 2005, 2007). This analysis, which can best be described as an outlier-robust extension of the traditional data envelopment analysis (DEA), reveals a spatial pattern of regional efficiency very similar to the East-West divide known in terms of per-capita income and labor productivity. In general, the efficiency of Western regions exceeds the efficiency of their Eastern counterparts. At the same time, results still differ significantly within the group of West and EastGerman regions. Therefore, we apply an extended kriging model, introduced by Kammann and Wand (2003) as the geoadditive approach, in the next step to further decompose the main drivers of regions' efficiency into a smoothed spatial and a non-spatial, arguably structural, factor.

The results of the study underline the importance of both spatial and structural factors for future funding. On the one hand, investments can indeed be justified on the grounds of the spatial factor. Regions in East Germany, for example, are still handicapped due to their location in the East. On the other hand, the appropriate type of funding heavily relies on the regions' internal economic structure. Regions with a sufficient ability to attract private capital,

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[1] The role of human capital as a determinant of labor productivity traces back to the seminal papers of Lucas (1988) and Romer (1990). A different line of research points to the importance of modern transport infrastructure. Nijkamp (2000) presents a comprehensive survey of relevant studies in the regional growth literature.

which in turn drives efficiency and the capacity utilization of the available region-specific factors (such as infrastructure and human capital), might benefit most from further investments into these factors. In contrast, regions with low efficiency scores (compared to the scores of the regions nearby) seem to lack the ability to attract private capital. In this case, public funding should focus on programs with the aim of attracting private capital in a more direct way.

The paper is organized as follows: Section 2 briefly discusses the role of traditional DEA and kriging models for regional studies. Section 3 introduces extensions of the traditional concepts and sets up the mathematical basis for the analysis. Application of the model follows in Section 4. Finally, Section 5 concludes with a summary of the main findings and policy implications.

2. THEORETICAL FRAMEWORK AND RELATED LITERATURE

DEA models in the regional context

The application of regional non-parametric frontier analysis traces back to a number of comparative studies on the economic performance of Chinese cities. In this context, Macmillan (1986) established DEA as an appropriate tool to measure the cities' efficiency. Charnes et al (1989) applied the same tool in order to monitor urban industrial performance and to assess regional planning tools in China. Eventually, the study of Seifert and Zhu (1998) used DEA to analyze the productivity growth of China's industries between the mid-1950s and the late 1980s.

The studies of China inspired further research in this field which includes, but is not limited to, analysis of the attractiveness of Japanese cities (Hashimoto and Ishikawa, 1993), the performance of manufactures in Mexico (Bannister and Stolp, 1995), the technical efficiency of U.S. farms (Thompson et al, 1990), the efficiency of public investments (Karkazis and Thanassoulis, 1998, Athanassopoulos, 1996) and the ranking of regions (Martic and Savic, 2001).

DEA methods have advantages and drawbacks. For a long time they were considered to be non-statistical techniques, so have been discredited in the world of econometricians for their apparent lack of statistical background. Today, DEA is recognized as an estimator and its statistical properties have been derived. Therefore inference, using bootstrap methods, is now available for building confidence intervals for efficiencies or testing hypothesis on returns to scale, etc. (see Simar and Wilson, 2008 for a recent survey on these topics and the references herein). Studies on regional efficiency have therefore often turned to other concepts such as stochastic frontier analyses or parametric efficiency measures, derived from regional production functions (e.g. Battese et al, 2004, Chen and Song, 2008, Kumbhakar et al, 1991, Meeusen and van den Broeck, 1977). The benefits of the frequently more challenging econometrics of parametric frontier analysis (compared to DEA models) were often seen in the lower degree of uncertainty of the results. This is true to the extent that there is no uncertainty as to the accuracy of the underlying regional production function (Stolp, 1990, p. 105). If the restrictive parametric specifications are wrong, all the inference is flawed and the interpretation of the results is uncertain.

DEA methods, in contrast, do not rely on the particular choice of a parametric model for the production function and for the stochastic part of the model (distribution of the error terms). DEA is nonparametric and the results are only determined by the data. This is considered an advantage for the present study, as the main aim is to receive directly observable evidence with respect to regions' efficiency, useful for the development of future funding schemes. Nonetheless, the strong orientation on the data comes along with another shortcoming. Since the estimated frontiers generally envelop all data, the sensitivity to outliers is problematic for most DEA models. This paper deals with this problem by using an outlier robust enhancement of DEA, the so-called order-α-frontier approach (Daouia and Simar, 2005, 2007).[2] As a consequence, the frontier does not reflect the maximum achievable output anymore, but some outliers are allowed to lie above the frontier. To our knowledge, this approach has not yet been applied in the context of regional efficiency.

Productivity spillovers among regions

The efficiency scores of the order-α-frontier approach point to a region's capacity utilization of the available infrastructure and human capital which is, to a large extent, driven by the region's ability to attract private capital. Therefore, efficient regions (with high capacity utilization) were considered preferred places for firm location in the past and are expected to be considered so in the future. In fact, the logic of maximizing profits even suggests that firms

[2] This paper presumes a basic familiarity with DEA. Among others, Boussofiane et al, 1991, Charnes et al, 1994 or Cooper et al, 2006 provide a good introduction into DEA. Fried et al (2008) present comprehensive recent surveys of many aspects of frontier estimation, including parametric approaches and DEA methods with its extensions and properties . The order-α-frontier approach is described in more detail in Section 3.

would all move to regions on the frontier in the long run. However, a rather high efficiency in using the available factors might turn into an over-utilization of the available factors, yielding congested infrastructure and a scarcity of specialist workers. Leaving aside external effects, such as noise and air quality, the provision of additional infrastructure (e.g. by directing funds into this region) could remove the bottleneck. Alternatively, firms could opt for a location in a neighboring region. This would be reasonable, if the firms expect productivity spillovers between the two regions.

From a theoretical point of view, the existence and relevance of those spillovers is not clear. A significant part of the non-spatial literature presumes that a region's level of productivity or income is, in line with the concept of the order-α-frontier approach, highly independent from the levels achieved in regions nearby. At the same time, a large body of the empirical literature in spatial econometrics is based on the concept of spatial dependence, which explicitly allows for spillovers among regions.[3] Some studies consider these two approaches complementary rather than conflicting and support the idea of modelling both simultaneously (among others, Abreu et al, 2005 and Ramajo et al, 2008). Following this line of thought, the order-α-frontier is succeeded by an extended kriging approach that accounts for the regions' spatial dependence. This, in turn, allows for decomposing the regions' overall efficiency scores into a smoothed spatial and a non-spatial structural part.

From kriging to geoadditive models

The concept of spatial dependence and the availability of spatial prediction has first been of interest in the broader field of geology. Among various techniques for spatial analysis that originated in this field, the so-called kriging can be considered one of the most popular methodologies to identify a spatial pattern prevalent in a given set of data.[4] This approach describes an interpolation technique for spatially-dependent variables which is still used in the field of mining and soil research but nowadays goes beyond this field. Interest in and applications for the kriging approach include data-intensive fields such as environmental monitoring or agriculture and forestry management (Diodato and Ceccarelli, 2004, Jost et al, 2005, Tavares et al, 2008).

The need to process ever more complex data sets points to one of kriging's major drawbacks:

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[3] Abreu et al (2005) present a comprehensive survey of studies using spatial and non-spatial econometric techniques and also discuss the importance of regional spillovers.

[4] See Trangmar et al (1985) and Goovaerts (1999). for surveys on studies dealing with kriging.

Computational cost increases rapidly with a rising complexity of the application. As a counter–measure, Hartman and Hössjer (2008) propose developing a kriging predictor based on Markov random fields, which would substantially decrease computation time.

Another drawback of pure kriging is the missing control of covariates. This problem can be addressed if an extended version is applied. The so-called *universal kriging* allows for the control of covariates by incorporating them directly into the model (Cressie, 1993). However, universal kriging is limited in a sense that covariate effects are presumed linear in nature. If non-linear relationships of the covariate with the response variable can be expected, Kammann and Wand (2003) propose a fusion of kriging and additive models to *geoadditive models*. Additionally, these types of models also allow for a more differentiated definition of neighborhood. In contrast to most kriging models, the concept of neighborhood is not limited to a binary definition (regions are neighbors or they are not) or a point-to-point relation (e.g. distance between the centers of two neighboring regions) but could account for more detailed data such as the length of the common border.

Recent applications of geoadditive models include the geographical variability of infants' health conditions in Massachusetts (ibid), gender-specific health status in Germany and forest health outcomes in Bavaria (Brezger and Lang, 2006).

In the present study, the geoadditive approach is used to decompose the regions' efficiency scores (derived from the order-α-frontier analysis) into a spatially driven and a non-spatial factor. The smoothed spatial factor shows the effect that is primarily determined by the general performance of a regions' greater surrounding area. The non-spatial structural factor gives an idea on a region's efficiency compared to the regions nearby.

3. MODEL SETUP

The analysis is carried out through a two-step approach. In a first step, an outlier robust DEA, the order-α-frontier analysis, is applied to identify the regions' efficiency. The second step seeks to decompose the efficiency by using a geoadditive regression analysis. We are aware that two-stage procedures in this setup should be carefully implemented (see Simar and Wilson, 2007 for details). First, a two-stage procedure can be applied only if some separable condition between the inputs x outputs space and the explanatory variable used in the second stage is reasonable. In our case here, it means that the set of feasible inputs x outputs is the same for all the regions.

Second, the inference on the results of the second stage regression is non-standard, because the response variable (the efficiency measures) are not directly observed but result from a complicated estimation procedure, implying inter-dependence, etc. The point is of no concern here because for the study at hand, the geoaddtive regression of the second stage remains, at this stage, at a descriptive level. We provide a geoadditive fit of the efficiencies without confidence intervals for the effect and/or testing hypothesis on the model. As suggested by Simar and Wilson (2007), bootstrap techniques would be helpful to provide such inferences; implementing this in the setup here certainly remains a topic for future research.

Order-α-frontier analysis

Traditional DEA has emerged as one of the most popular instruments to identify efficiency boundaries of firms, production branches or regions. At the same time, the approach is often found to be rather sensitive to extreme observations. The order-α-frontier analysis aims to overcome this shortcoming by defining a frontier function that excludes outliers. The mathematical formulations below reflect a reduced version of this enhanced DEA model that is described in full detail by Daouia and Simar (2005, 2007).

Presuming that regions improve their efficiency more likely by growing outputs rather than decreasing inputs, we focus on the output-oriented version of the model. Equations (1) to (3) briefly set up the traditional model which serves as a starting point for the extended model, further specified by equations (4) and (5).

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

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

The boundaries of Ψ reflect maximum outputs that can be generated with given inputs and therefore define the regions' efficient frontier as:

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

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:

(3) $\lambda(x,y) = \sup\{\lambda | (x,\lambda y) \in \Psi\} = \sup\{\lambda | \lambda y \in Y(x)\}$

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.

In order to determine Ψ, which is generally unknown, nonparametric estimators have been proposed. One such estimator is the free disposal hull (FDH, Deprins et al, 1984), which relies on a minimal set of assumptions[5]. However, as most of these estimators envelop all data points, traditional FDH/DEA is rather sensitive to extreme observations.

More robust estimators might solve this problem by treating outliers in a different way. Instead of defining the efficient boundary according the uppermost technically achievable output (for any given input), extreme observations are allowed to lie above a partial frontier (Cazals et al, 2002). In this context, Aragon et al (2005) introduced the concept of the order-α partial frontier (α∈[0,1]) for a univariate output. Daouia and Simar (2007) extended the concept for a full multivariate setup, which is applied for the present study.

With $S_{Y|X}(y\,|\,x)$ defined as the probability $\text{Prob}(Y \geq y\,|\,X \leq x)$ and $F_X(x)$ as the probability $\text{Prob}(X \leq x)$, Daouia and Simar (2007) define the order-α-quantile output efficiency score for each unit $(x,y) \in \Psi$ as:

(4) $\lambda_\alpha(x,y) = \sup\{\lambda | S_{Y|X}(\lambda y\,|\,x) > 1-\alpha\}$ for $F_X(x) > 0$ for α∈ [0,1] [6]

Following this approach, note that each unit is only benchmarked against units disposing of similar or lower input levels.[7] 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 ≤ 1-α. Units below the efficient boundary ($\lambda_\alpha(x,y) > 1$) are considered inefficient. This means a unit with similar or lower input delivers higher output with a

[5] The FDH estimator only relies on free disposability assumptions for the inputs and the outputs. If convexity of Ψ is also assumed, the DEA estimator is more appropriate.

[6] The efficiency score converges from below to the Debreu-Farell output efficiency measure λ(*x,y*) as α tends to 1.

[7] 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 (λ_α(x,y) = 1).

probability > 1-α. Conversely, units above the frontier ($\lambda_\alpha(x,y) < 1$) could reduce their outputs but would remain output efficient at the α level.

The applied nonparametric estimator of $\lambda_\alpha(x,y)$ is obtained by substituting $S_{Y|X}(y\,|\,x)$ with its empirical correspondent $\overline{S}_{Y|X,n}(y\,|\,x)$, 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 $\overline{\lambda}_{\alpha,n}(x,y)$.

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

The properties of this estimator have been established in Daouia and Simar (2007) ($\sqrt{n}$-consistency and asymptotic Normal distribution). The strength of this approach becomes particularly apparent for samples with extreme observations as they might easily occur for a sample of regions. Note that if α tends to 1, this estimator converges to the FDH estimator of the full frontier, but the latter will envelop all the data points. Furthermore, the approach accounts for the heterogeneity of the sample, as each region is only compared with regions whose input levels are equal or worse. This in turn implies that the number of comparable units decreases with the increasing number of considered inputs.

Geoadditive regression analysis

The applied order-α-frontier analysis generally presumes a high independence of the units' activities. However, the assumption is at least questionable if the sample encloses spatial entities. By contrast, we presume the existence of productivity spillovers caused, for example, by knowledge spillovers or the easy access to modern transport infrastructure serving neighboring regions (Bronzini and Piselli, 2009, Cohen, 2010, Ramajo et al, 2008). As a consequence, the regions' efficiency is – at least to some extent – driven by neighbors' performance. At the same time, neighborhood cannot be considered the only determinant but is complemented by intra-regional drivers. In this context, the geoadditive approach outlined below aims to identify the relevance of the different drivers by decomposing efficiency into a spatial and a non-spatial effect.

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

The first step seeks to define 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. Thus, the smoothing algorithm, which is weighted by the length of the common border (ω_{rs}), presumes 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 to substitute a usual parametric with a flexible nonparametric parameter, containing in this case spatial information (Fahrmeir et al, 2001, Hastie and Tibshirani, 1990). Since the focus of the present study is exclusively on the spatial distribution of efficiency as the response variable, no parametric covariables are considered. Therefore, the nonparametric regression model is set up in the following way (Fahrmeir and Lang, 2001, Kammann and Wand, 2003):

$$(6) \qquad \overline{\lambda}_{\alpha,n}(x_i, y_i) = f_{geo(i)} + f_{rand\,(i)}$$

where $\overline{\lambda}_{\alpha,n}(x_i,y_i)$ is the empirical efficiency score of region i (defined by equation (5)) 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.[8]

To smooth the regions' spatial factor, a penalizing term, based on the least square method (PLS), is introduced in equation (7). In this preliminary step, the weights ω_{rs} remain unconsidered.

$$(7) \qquad PLS(\mu) = \sum_{i=1}^{n}(y_i - f_{geo(s_i)})^2 + \mu \sum_{s=2}^{d} \sum_{r \in N(s), r<s} (f_{geo(r)} - f_{geo(s)})^2$$

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.

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

In this context, the penalizing approach, which includes the minimization of *PLS(μ)*, can be interpreted in Bayesian way (Fahrmeir and Lang, 2001, Brezger and Lang, 2006). This in turn yields markov random fields. Therefore, the application of the model follows a Bayesian approach (with fully Bayesian inference) and is simulated by markov-chain-monte-carlo (MCMC) technique.[9]

Finally, the expected value γ_i of the nonparametric spatial factor $f_{geo(i)}$ can be 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.[10]

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

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.

To illustrate the order-α-frontier and the geoadditive regression analysis, both methodologies are applied to identify and decompose the efficiency of German regions in the next section.

4. APPLICATION

Efficiency of German regions

The identification of German regions' efficiency follows the mathematical model of the

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

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

order-α-frontier analysis outlined in Section 3. For this purpose, DMUs as well as inputs and outputs are defined first, followed by a discussion of the results and a brief sensitivity analysis for the parameter α.

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 could be considered at four regional levels of aggregation. NUTS 1 defines the most aggregated regional level and complies, in the case of Germany, with the Federal States. NUTS 2 is the basic administrative unit chosen by the EU for a broad set of regional policies. NUTS 3 corresponds to the county level and finally NUTS 4, the most disaggregated spatial unit, complies with the community level. With regard to data availability the presented study is based on the NUTS 3 level which, in the case of Germany, encloses 439 regions.[11]

The input-output system in regional frontier analyses generally accounts for variables that reflect and determine socio-economic performance of the considered territorial units.

On the output-side, the gross regional product (GRP), total employment, private investments and trade volumes can be considered (Athanassopoulos, 1996, Karkazis and Thanassoulis, 1998). However, due to the different sizes of the considered regions (in particular in terms of population), the significance of these indicators is sometimes limited. Therefore, intensive variables such as labor productivity or per-capita income might reflect economic performance in a more appropriate way for comparative regional analyses (Dunford, 1993, LeSage and Fischer, 2008). The present study follows this research stream and defines the output indicator according the per-capita income for the year 2004.

Following the idea that regional production (and subsequently income) is mainly determined by the regions' endowment with, in the medium run, immobile factors, input indicators are

[11] In fact, Germany counts 440 NUTS 3 regions. However, the county of Rügen has no common border with any other county and remains for technical reasons unconsidered.

defined by the region-specific human capital and transport infrastructure for the year 2004 (Biehl 1995, Bronzini and Piselli 2009).

With regard to infrastructure capital, the input factor accounts for the intra-regional equipment with transport infrastructure (defined by the sum of the weighted road and railway density and the potential capacity utilization[12]) and the regions' connectivity (determined by the minimal travel time between the considered regions and other regions within and outside of Germany). [13]

The regions' human capital is further divided into a quantitative factor and a qualification indicator. The qualification indicator derives from the weighted educational achievements of the available workforce. The quantitative factor could either be defined as the absolute number of employees or the share of employees in the regional population. On the one hand, the relative share seems to be attractive as the factor would not be affected by the regions' different sizes of population. On the other hand, the size effects might be of interest as they partly reflect the regions' characters as metropolitan or rural areas. Based on the results of a simple OLS regression, the absolute number seems to be the more appropriate indicator. The results, presented in Table 1, also confirm the presumed positive and significant correlation of per-capita income and the other inputs.

TABLE 1: Correlation of the input variables with the per-capita-income

	Infrastructure capital	Human capital		
		Qualification	No. of employees	Share of employees in total population[1]
Correlation co-efficient (Pearson)	0.579**	0.333**	0.163**	0.042
Significance	0.000	0.000	0.001	0.378
N	439	439	439	439

[1] Indicator remains unconsidered for the presented order-α-frontier analysis

** The correlation is significant on the level of 0.001

[12] The weighting reflects the differences of construction and maintenance cost (e.g. Reynaud and Braun, 2001, Williams, 2002).

[13] The exact definition of all input indicators is given in the Appendix.

Despite the relevance of the chosen inputs, it can indeed be argued that the NUTS 3 regions' role in the decisions making process on new infrastructure projects or educational investments is limited, which in turn conflicts with the regions' definition of decision-making units. However, since we apply the output-oriented version of the order-α-frontier analysis, regions decide how to use a *given* infrastructure and human capital and not whether or not to increase the inputs. In this sense a region, or more precisely the stakeholders of a region, can indeed be more or less efficient in using the defined inputs.

Following the model outlined in Section 3, the first findings derive from the application of the order-α-frontier analysis.[14] Figure 1 shows the regional efficiency for $\alpha = 0.95$.

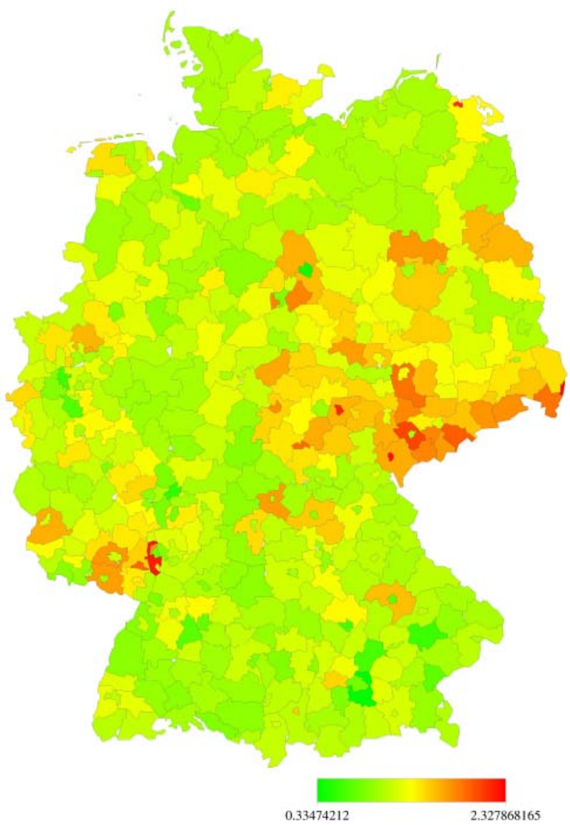


FIGURE 1: Efficiency score $\overline{\lambda}_{\alpha,n}$ of German NUTS 3 regions, order-α-frontier analysis, 2004

A region is considered comparatively inefficient if one or more other regions equipped with a similar or worse level of infrastructure and/or human capital generate(s) higher levels of output (GRP per capita). These regions are red-shaded. On the contrary, the green-shaded regions show the highest level of efficiency, as they deliver comparatively high per-capita

[14] In the context of this paper, efficiency only refers to the considered input and output variables. Thus, rather inefficient regions could indeed be efficient in another context.

income with the given inputs.

Following the order-α-frontier analysis, a unit (x,y) is efficient at level α, if another unit with lower inputs dominates the unit with a probability ≤ 1-α. As a consequence, the analysis gains in robustness versus outliers. At the same time, the results are mainly driven by the choice of α, which in turn requires a careful definition of α.

For the presented study the selection of α = 0.95 and this choice is to some extent arbitrary. The literature on robust frontiers, like the order-α frontier we use here, does not provide formal rules for selecting the order α. Common sense often leads to the selection of values near the usual 95% level. It is also recommended to proceed to a sensitivity analysis (the computing time is quite negligible) and compare the results for values near the usual 90% level, and look at the percentage of data points that remain outside the order-α frontier. Simar (2003) suggests this approach to detect outliers in a more systematic way. Therefore, first we compare the efficiency scores of the traditional FDH (α = 1) with the scores derived from the order-α-frontier analysis for α = 0.99, α = 0.95 and α = 0.9 respectively. The results, illustrated by Figure 2, show that efficiency scores differ clearly. This, in turn, points to the existence of a significant number of outliers in the sample when α = 0.95 and even when α = 0.99.[15] For this reason, the analysis indeed benefits from the application of an outlier-robust model.

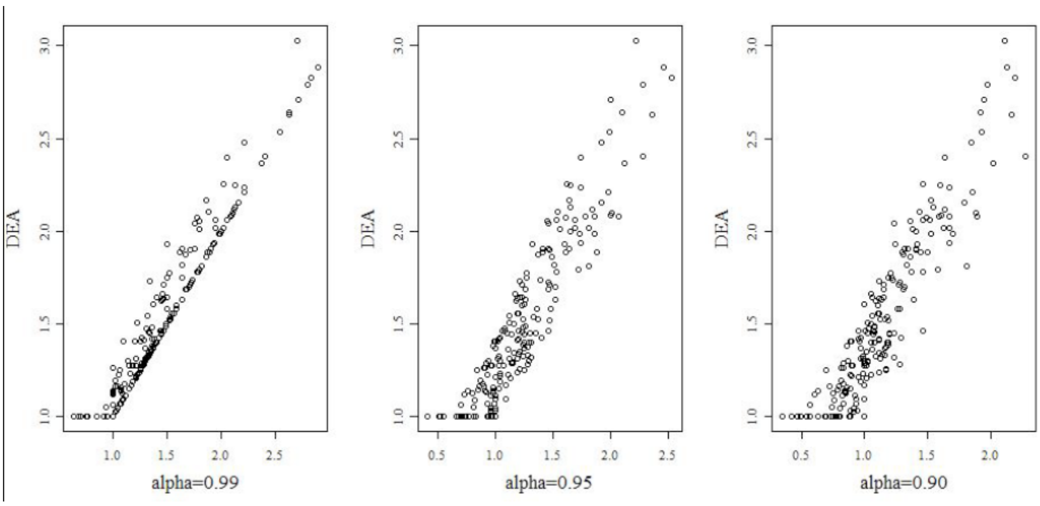


FIGURE 2: Efficiency scores for traditional FDH and order-α-frontier analysis.

[15] According to Simar (2003), the potential outliers are those points having α-scores less than 1 (points that remain outside the estimated α-frontier) even when α is converging to 1 (when $\alpha = 1$, there are no such points). These points appear on the bottom left of Figure 2.

To complement the sensitivity analysis, the efficiency scores for α = 0.95 are plotted against the scores for α = 0.99 and α = 0.9 respectively (figure 3).

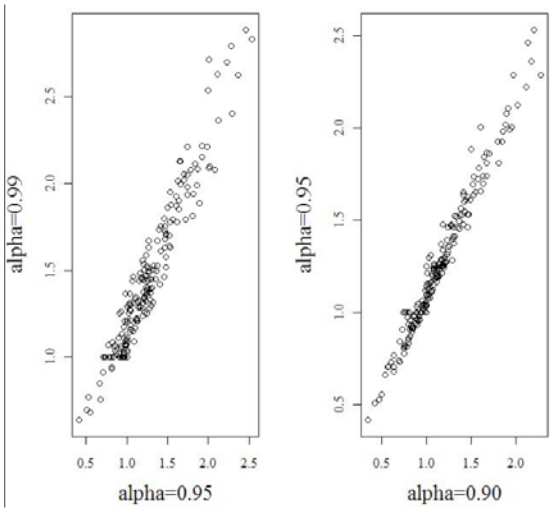


FIGURE 3: Efficiency scores for α = 0.95 against the scores for α = 0.99 and α = 0.9

The left plot (0.95 vs. 0.99) is characterized by a relatively strong difference of the scores. In contrast, the spread is considerably lower in the right plot (0.95 vs. 0.9). This means that the number of outliers that are allowed to lie above the frontier significantly increases, if we opt for α = 0.95 instead of α = 0.99, but hardly changes if α is set to 0.9 instead of 0.95. This is confirmed by looking at the bottom left parts of the pictures in Figure 2. Thus, for the sample at hand, the option for α = 0.95 seems to be an appropriate choice.

Decomposing the regions' efficiency

The findings of the order-α-frontier analysis, illustrated by Figure 1, suggest a likely dependency of a region's efficiency with the performance of its greater neighboring area. Consequently, a region surrounded by very efficient regions might deliver above-average results compared to the full sample, even if the region's performance is below-average relative to nearby regions.

The application of geoadditive regression analysis, described in Section 3, allows for a more in-depth analysis of this effect by decomposing the regions' efficiency (Figure 1) into a spatial and a non-spatial factor respectively. Following the geoadditve regression analysis, Figure 4 identifies the smoothed spatial effect.

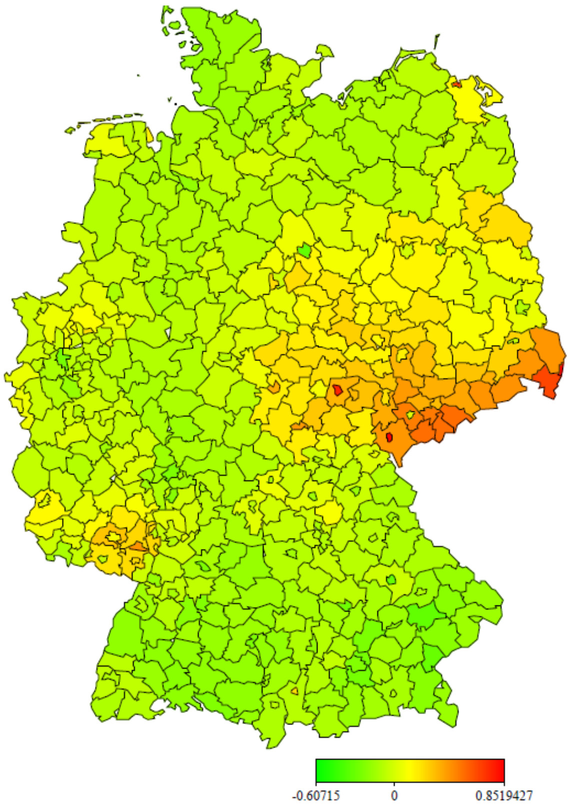


FIGURE 4: Efficiency of German NUTS 3 regions, smoothed spatial factor $f_{geo(i)}$, 2004

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.

The findings reveal a clear spatial pattern and identify, 20 years after the unification, a clear East-West divide.[16] Interestingly, some North-Eastern and South-Western regions hardly fit into this general picture.

The low efficiency scores found for the Western and South-Western regions in Rhineland Palatinate reflect the rather fragile economic situation in these regions that comes along with structural deficits, high unemployment rates and comparatively low per-capita income. The surprisingly positive results for the North-Eastern regions of Mecklenburg-Western Pommerania can be explained by the logic of the frontier approach. Efficiency turns out to be relatively high, as their rather low per-capita income, comes along with a low endowment

[16] Remarkably, the findings on efficiency hardly support the idea of a North-South divide for West German regions.

with infrastructure and human capital.

The findings on the spatial factor (Figure 4) clearly correspond to the rough pattern of the overall efficiency scores (Figure 1). At the same time, the smoothing algorithm partly veils regional distinctions. It can therefore be concluded that the regions' efficiency is also driven by a non-spatial effect. This effect, illustrated by Figure 5, can be interpreted as a structural effect.

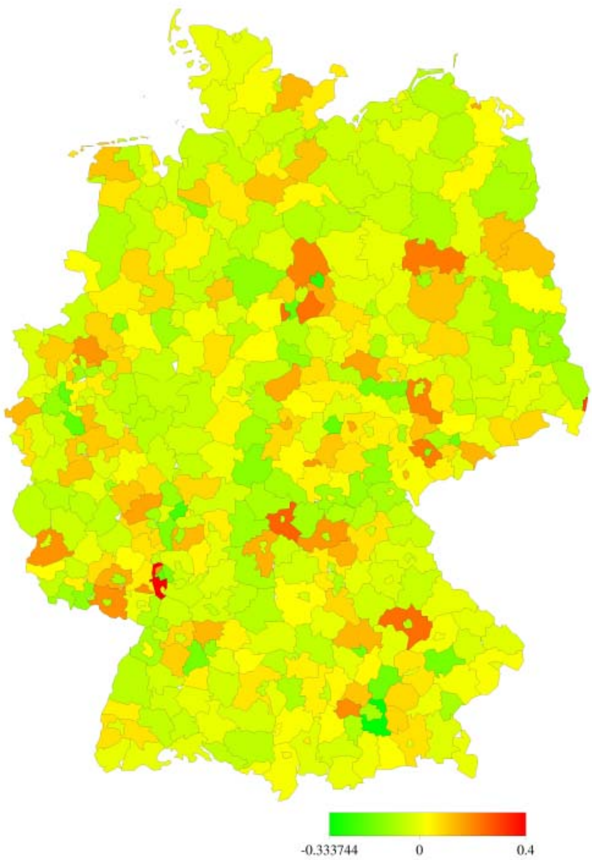


FIGURE 5: Efficiency of German NUTS 3 regions, non-spatial structural factor $f_{rand(i)}$, 2004

According to Figure 5, 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 infrastructure and/or human capital generate(s) higher levels of per-capita-income. By contrast, a green-shaded region is efficient compared to its nearby regions.

Compared to Figures 1 and 4, the East-West divide almost vanishes in Figure 5. While some Eastern regions, particularly in the greater areas of Magdeburg, Dresden or Leipzig, turn out to be relatively efficient compared to the regions nearby, the opposite trend can, to a minor extent, be observed for some West German regions. This is particularly evident for the greater area of the Southern regions of Regensburg and Schweinfurt, the Northern regions Hannover and Wolfsburg as well as the regions east of Ludwigshafen.

The effect can partly be explained by the regions' character as manufacturing centers or commuter towns. The high efficiency of Ludwigshafen and Wolfsburg and the low score of their neighbors, for example, are certainly driven by BASF and VW respectively. While the headquarters and main production sites are located in Ludwigshafen and Wolfsburg, employees tend to live in the surrounding regions. A similar effect can be observed for Regensburg and Schweinfurt, where most firms are located in the urban centers and employees commute from neighboring rural counties.

However, since the number of employees defines one of the input factors, the efficiency analysis accounts at least to some extent for the regions' character as manufacturing centers (with a high number of employees) or commuter towns (with a low number). Thus, a low (high) non-spatial efficiency might point to a structural deficit (advantage). According to Figure 5, regions with a structural advantage include (but are not limited to) the greater areas of Hannover, Cologne, Frankfurt and Munich as well as South-Western regions close to the Black Forest. In contrast, regions in the Ruhr area (e.g. Recklinghausen, Coesfeld, Unna or Wesel) and some East German regions clearly suffer from a structural deficit (see Appendix for a map with the regions discussed in this section).

As for the smoothed spatial factor, the identified pattern for the non-spatial factor (Figure 5) and the picture for the overall efficiencies are alike. In order to analyze the importance of the decomposed factors as drivers for the overall efficiency score, the final step is a multiple linear regression with the efficiency score based on the order-α -frontier analysis as explained and the two decomposed factors as explaining variables.

TABLE 2: Multiple linear regression analysis with overall efficiency scores as explained variable

	Spatial factor	Non-spatial (structural) factor	Model fit	
			multiple R^2	adj. R^2
Correlation co-efficient (Pearson)	0.823^{**}	1.110^{**}	0.71	0.70

Significance	0.000	0.000
N	439	439

** The correlation is significant on the level of 0.001

Even if we know that p-values computed at the second-stage regression must be taken with care (see Simar and Wilson, 2007), the significance level is so small that we can conclude safely from the results, presented in Table 2, that both spatial and non-spatial factors have a similar positive and highly significant impact on overall efficiency. Here again, as mentioned above, some refinement would be obtained by using a more appropriate bootstrap procedure still to be implemented in this new setup.

5. POLICY IMPLICATIONS

The provision of public goods, such as investments into modern transport networks or institutional education, plays a crucial role in a broad set of regional policy tools.[17] The main aim of this instrument is twofold. On the one hand, the economic motive seeks high productivity for funds invested in each region (Castells and Solé-Ollé, 2005). A policy devoted to this *efficiency* argument would aim to maximize return on public investments and would indeed prefer to give financial aid to the efficient regions.

On the other hand, the *equity* argument justifies the redistribution of funds in order to foster cohesion. In this case, the relative per-capita income is often chosen as a yardstick that allows us to draw a clear parting line and to allocate funds transparently. However, the distribution of financial aid could, at least to some extent, be based on the degree of efficiency as well. Following the cohesion argument, the funding should focus on inefficient rather than efficient regions (Athanassopoulos, 1996, Camagni, 1990).

The present paper follows this idea and identifies, in a first step, the regions' efficiency by applying a recently developed outlier robust enhancement of the DEA – the order-α-frontier analysis (Daouia and Simar, 2005, 2007). The results presume a generally lower efficiency of East compared to West German regions. However, some regions in West Germany, in particular in Rhineland-Palatinate turn out to be inefficient as well.

[17] See for example Nijkamp (2000) for a summary of the current discussion on the economic impacts of public infrastructure investments.

A decomposition of the efficiency scores, based on geoadditive regression analysis, revealed in a second step that the results are partly driven by a spatial and a non-spatial factor. Thus, some regions are primarily considered inefficient due to the low efficiency levels of nearby regions rather than to their own failures. On the other hand, some regions might be weak from a structural point of view but appear relatively efficient since they benefit from the high efficiency of neighboring regions.

The consideration of these results yields a more differentiated funding scheme. Regions whose low overall efficiency can be explained by their location in space rather than their internal structures are more successful in attracting private capital compared to the regions nearby with similar input levels. For these regions, the provision of public goods can be considered an appropriate instrument for alleviating existing or potential bottlenecks. On the contrary, this instrument loses importance for regions whose low efficiency in using existing region-specific inputs is driven by their location in space and their economic structure. In this case the potential bottleneck can be seen in the regions' insufficient ability to attract private capital. Therefore, these regions benefit most from funds used for programs that attract private capital in a more direct way (e.g. SME programs).

APPENDIX

Definition of inputs

The internal part of infrastructure capital I^{in} of region i is defined according equation (A1):

$$\text{(A1)} \quad I_i^{in} = \frac{p_i}{r_{\omega,j}} + \eta \cdot \frac{r_{\omega,j}}{a_i},$$

where $r_{\omega,i,}$ denotes the weighted length of road and rail network (in km), a_i the area (in sqkm), and p_i the population of region i. The leveling factor η is chosen in a way that the average road density equals the product of average capacity utilization and leveling factor (Biehl, 1995).

The external part of infrastructure capital I^{ex} is defined as the regions' centrality. For this purpose, the travel time between any German region i and any region j within the EU as well as the corresponding markets (measured by GRP) are taken into account by equation (A2):

(A2) $$I_i^{ex} = \sum_{j=1}^{m} GRP_j \cdot e^{\omega \cdot \min(t_{rail}(i,j), t_{road}(i,j))} ,$$

where m equals the number of European NUTS 3 regions (EU 25), t_{rail} and t_{road} the travel time between region i and j by rail and road respectively. Parameter ω is a weighting factor that fulfils the following condition:

(A3) $e^{\omega T} = 0.5$ for T=180 minutes.

Thus, the GRP, which can be reached within 180 minutes, is weighted by 0.5.[18] Smaller weights are attributed to the GRP further away and higher weights account for the GRP that can be reached faster (Schaffer and Siegele, 2009).

The regions' human capital relies on a quantitative and a qualitative factor. The quantitative input is defined by the regions' number of employees. Since the number of self-employed persons is not available for all regions, the employees *subject to social insurance* are taken as a proxy for the total number of employees. Thus, we presume a rather constant ratio of employees subject to social insurance and self-employed persons (which can indeed be observed for the regions where both numbers are available).

The qualification indicator Q is determined by the educational achievements of the regional workforce. Following the International Standard Classification of Education (ISCED) the work force is subdivided into three groups in a first step. Members of the workforce with the highest educational achievements corresponding to lower secondary education belong to the first group (ISCED 1 and 2). The second group encloses all persons with upper- and post-secondary (non-tertiary) education (ISCED 3 and 4). Finally, the third group is defined by persons with tertiary education (ISCED 5 and 6).

The next step is the weighting of the educational achievements according to the average time use of students and teachers needed to obtain the corresponding qualification level level. The

[18] The half-value period has been set to 180 minutes, which is often cited as acceptable travel time for daily business trips and used for calibration of passenger transport models (e.g. Schoch, 2004). The analyses with parameters that correspond to a half-value period of 120 and 90 minutes respectively hardly affect the results on efficiency.

weighting factor is set to 1 for educational achievements of the first group and reaches a value of about 1.8 and 2.6 for the second and the third group respectively.[19]

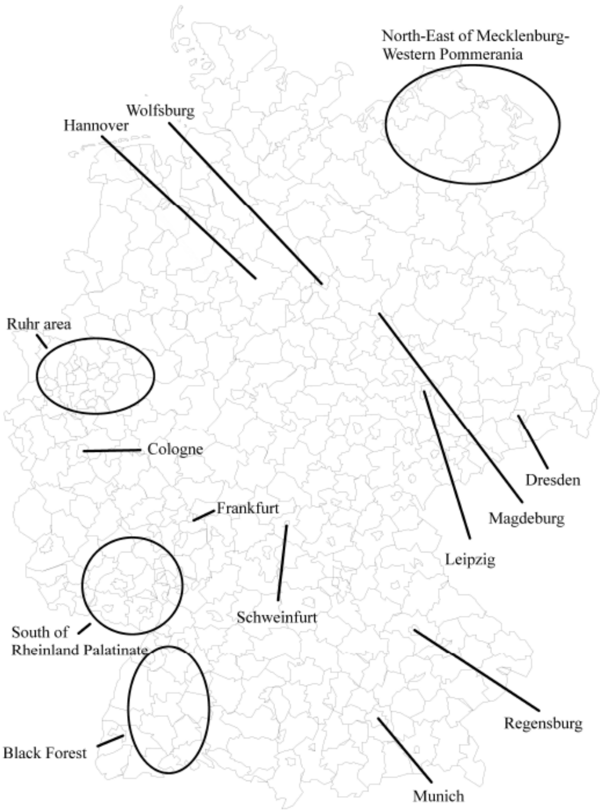
Thus, the human capital indicator Q can be calculated according the following formula:

$$Q_i = \frac{\sum_{j=1}^{3} \omega_j \cdot f_{ij}}{\sum_{j=1}^{3} f_{ij}} \tag{7}$$

where ω_j equals the weighting factor according the educational group j and f_{ij} denotes the members of workforce in region i with educational achievements corresponding to group j .

[19] See Schaffer and Stahmer (2006) for a detailed derivation of the weighting factors.

Map of Germany with regions mentioned in the paper



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