Regional environmental efficiency and economic growth: NUTS2 evidence from Germany, France and the UK

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Abstract

This paper by applying nonparametric techniques measures spatial environmental heterogeneities of 98 regions from Germany, France and the UK. Specifically environmental performance indexes are constructed for the 98 regions (NUTS 2 level) identifying their ability to produce higher growth rates and reduce pollution (in the form of municipal waste) generated from regional economic activity. By applying conditional stochastic kernels and local constant estimators it investigates the regional economic activity – environmental quality relationship. The results indicate several spatial environmental heterogeneities among the examined regions. It appears that regions with higher GDP per capita levels tend to have higher environmental performance.

Keywords: Regional environmental efficiency; directional distance function; conditional stochastic kernel; nonparametric regression.

JEL classification: C6, O13, Q5.

1. Introduction

According to Le Gallo and Ertur (2003) *spatial heterogeneity* indicates differences of economic behavior across space which in turn can create characteristic spatial patterns of economic development under the form of spatial regimes: a cluster of rich regions (the core) being distinguished from a cluster of poor regions (the periphery). Similarly, in this paper we assume that *spatial environmental heterogeneity* indicates differences of environmental policy[1] across space which in turn can create characteristic spatial patterns of environmental performance under the form of spatial environmental policy regimes: for instance, a cluster of high development-low pollution regions being distinguished from a cluster of low development-high pollution regions. In addition environment and space, or environmental quality and regional development are interrelated, which is reflected on regional environmental policy analysis.

The nexus between environmental quality, economic activity and growth has been examined mostly in a non-regional setting (Batabyal and Nijkamp 2004, p. 295)[2]. The relationship between economic growth and environmental quality has been examined over the years in a country level rather than regionally. In a country level, Grossman and Kruger (1995) found a U-type (Environmental Kuznets Curve-EKC)[3] relationship between economic activity and environmental quality. Over the years this finding has found support from several country levels studies (among others Selden and Song 1994; Ekins 1997; Stern 1998, 2002, 2004; Ansuategi and Perrings 2000;

[1] According to Batabyal and Nijkamp (2004) regional environmental policy is a tradeoff between economic development and environmental quality.
[2] One of the first studies considering a theoretical model of multiregional growth, environmental processes, and multiregional trade was conducted by van den Bergh and Nijkamp (1998) indicating that when multiregional externalities exist, then it may not be possible to sustain growth in either region or in the global system.
[3] Kuznets (1955) showed that during the various economic development stages, income disparities first rise and then begin to fall.

Cavlovic et al. 2000; Andreoni and Levinson 2001; Antweiler et al. 2001; Bulte and Soest 2001; Dasgupta et al. 2002; Halkos 2003).

The tradeoff between environmental quality and economic development has been first modeled by Färe et al. (1989) with the use of distance functions in a nonparametric setting. It was the first model measuring environmental technology in a production function framework. In addition the model introduced by Färe et al. (1989) has treated pollutant as output of the production process and by imposing strong and weak disposability developed environmental performance indicators (hereafter EPIs). Later, Tyteca (1997) introduced another EPI based on the same principles as Färe et al. (1989) but with different assumptions. Since then, the construction of EPIs has been introduced by several papers that incorporate them into their analysis.

Furthermore, Chung et al. (1997) using the weak disposability assumption of outputs constructed a Malmquist–Luenberger index, creating for the first time environmental productivity indexes. Following the modeling principle by Färe et al. (1989), several other country level studies have examined the relationship between economic growth and environmental performance (Zaim and Taskin 2000; Taskin and Zaim 2001; Zofio and Prieto 2001; Zaim 2004; Managi 2006; Yörük and Zaim 2006; Picazo-Tadeo and García-Reche 2007).

Following those studies, our paper tries to contribute to the literature by examining the environmental quality-economic activity and growth relationship in a regional context rather than in a country level. According to Rupasingha et al. (2004) all the EKC country level studies have ignored the spatial relations among the units. The importance of spatial dimensions in environmental measures has been highlighted by several studies (Bockstael 1996; Goodchild et al. 2000; Anselin 2001). Anselin (2001) suggests that country level environmental studies can be biased due to the scale mismatch of the various data used. This shortcoming has been also highlighted by several authors on studies examining the EKC hypothesis with the use of country level data (Grossman and Krueger 1995; Stern et al. 1996; Vincent 1997; Carson et al. 1997).

Therefore, by contributing to the literature, our study constructs regional environmental efficiency (hereafter REE) indicators for ninety eight regions of the UK, France and Germany (at NUTS 2 level). Additionally by applying several nonparametric techniques the EKC hypothesis is investigated by analyzing the effect of regional GDP per capita on the obtained regional environmental efficiency levels of these regions.

2. A brief overview of regional studies using nonparametric techniques

As suggested by several authors (Førsund and Sarafoglou 2002; Førsund et al. 2009), Hoffman's (1957) discussion regarding Farrell's (1957) paper was the first to indicate that linear programming can be used in order to find the frontier and estimate efficiency scores, but only for the single output case. Later, Boles (1967, 1971) developed the formal linear programming problem with multiple outputs identical to the constant returns to scale (CRS) model in Charnes et al. (1978) who named the technique as data envelopment analysis (hereafter DEA).

The applicability of DEA for evaluating spatial phenomena using multiple criteria has been highlighted by several authors (Macmillan 1986; Halkos and Tzeremes 2010, 2011; Suzuki et al. 2010). Several studies have used DEA methodology in order to investigate and analyze regions. For instance Maudos et al. (2000) have applied DEA methodology in order to investigate technical efficiency of Spanish regions for the time period of 1964-1993. They have found evidences that intra-sector efficiency gains were a significant source of convergence among the

Spanish regions. Zabala-Iturriagagoitia et al. (2007) have used DEA methodology in order to evaluate regional innovation system performance using regional data from the European Innovation Scoreboard for the time period of 2002-2003. Their results indicate that a higher technological level of a region will result in a greater need for system coordination. Enflo and Hjertstrand (2009) used a DEA bootstrapped model in order to investigate European regional productivity. They found that DEA methodology provided robust results with respect to spatial autocorrelation and is proved to be stable in terms of bias corrections.

Honma and Hu (2009) investigated energy productivity changes of 47 regions in Japan for the time period of 1993-2003. By applying a DEA total-factor energy productivity change index they have found evidences that most regions identified as frontier shifters are located outside Japan's four major industrial areas. Pulina et al. (2010), using variation of DEA models incorporating panel data, analyzed the efficiency of hotels across 20 Italian regions over the time period 2002-2005. They have found major inefficiencies among the hotels across the regions. Zhong et al. (2011) applied constant (CRS) and variable returns to scale (VRS) input oriented DEA models in order to evaluate the performance of R&D investments in industrial enterprises for 30 Chinese provinces. Their results indicate high inefficiencies of R&D investment among the industrial enterprises.

Many studies have used DEA methodology in order to measure environmental performance of a decision making unit (DMU). Furthermore, several modeling approaches have been applied in order for the pollutant to be treated properly in an environmental production framework.

One of the ways that the bad output can be modelled appeared in the original work by Färe et al. (1989) who assumed strong (for desirable outputs) and weak (for undesirable outputs) disposability treating environmental effects as undesirable outputs in a hyperbolic efficiency measure. Generally the property of weak disposability of detrimental variables is well known and has been used in several formulations (Färe et al. 1996, 2004; Chung et al. 1997; Tyteca 1996, 1997; Zofio and Prieto 2001; Zhou et al. 2006, 2007).

But, although this approach is widely accepted among the environmental economists it has faced several criticisms (Hailu and Veeman 2001; Färe and Grosskopf 2003; Hailu 2003). In fact the whole debate according to Kuosmanen (2005, p. 1077) stands for the 'operationalization of weak disposability in empirical production analysis'. In addition Kuosmanen (2005) has further criticized the implementation of the weak disposability property indicating that the disposability axiom requires the use of K different abatement factors (one of each observed activity in the sample).

Färe and Grosskopf (2009) replied claiming that a single abatement factor is sufficient. However, Kuosmanen and Podinovski (2009) proved that a single abatement factor does not suffice to capture all feasible production plans and that Kuosmanen's (2005) technology is the correct minimum extrapolation technology under the stated axioms. On the other hand, Seiford and Zhu (2002) developed a radial DEA model, in order to improve efficiency via increasing desirable and decreasing undesirable outputs. They have introduced a linear monotone decreasing transformation and thus undesirable outputs can be treated as desirable.

However, Färe and Grosskopf (2004) commented on that transformation claiming that Seiford and Zhu's methodology provide different efficiency results due to the fact that it does not resort to ad hoc treatment of undesirable outputs as inputs (as a result of the imposition of strong disposability assumption for all outputs).

Furthermore, Färe and Grosskopf suggested an alternative approach based on directional output distance function. Later, Seiford and Zhu (2005) replied to the critic made and proved that Färe and Grosskopf's proposed model based on directional output distance function is very similar to the weighted additive model (Ali et al. 1995; Thrall 1996; Seiford and Zhu 1998) where the bad outputs are treated as controllable inputs[4].

Given the modelling considerations raised, our study applies the weak disposability assumption using directional distance functions as has been suggested by several scholars (Färe et al. 1989, 1996, 2004; Chung et al. 1997; Tyteca 1996, 1997; Zofio and Prieto 2001). Following this approach and similar to our study Watanabe and Tanaka (2007) used the directional output distance function in order to measure the environmental efficiency of Chinese industry at the provincial level for the period of 1994 to 2002. In a second stage analysis regressing the environmental efficiency scores using a Tobit model, they have found that that a province's industrial structure has significant effects on its efficiency level. Bian and Yang (2010) examined the environmental efficiency of 30 provinces in China using a modified DEA model indicating several inefficiencies among the Chinese provinces. Similar results have been also reported by Guo et al. (2011) using a DEA model for 29 Chinese provincial administrative regions for the time period 2005-2007.

Based to our knowledge there is not any study that has first measured regional environmental efficiencies (especially for EU regions) and second examined regional environmental efficiency levels against regional economic growth in order to test the EKC hypothesis.

[4] In fact many studies have used the undesirable output as input when measuring environmental efficiency, treating in this way the pollutant as cost variable (Pitman 1981; Cropper and Oates 1992; Reinhard et al. 2000; Dyckhoff and Allen 2001; Hailu and Veeman 2001; Korhonen and Luptacik 2004; Mandal and Madheswaran 2010).

3. Data and Methodology

In our analysis we use data collected from two different regional databases (Eurostat[5] and OECD[6]) for the year 2005. Based on several other studies similar to ours (Färe et al. 1989, 1996, 2004; Chung et al. 1997; Tyteca 1996, 1997; Taskin and Zaim 2001; Zofio and Prieto 2001; Zaim 2004; Managi 2006; Yörük and Zaim 2006; Picazo-Tadeo and García-Reche, 2007) the two inputs used in our analysis are total regional labour force (employed people-all NACE activities) and regional gross fixed capital formation (in million €). In addition the two outputs used in our study are the regional gross domestic product (million PPS- as 'good' output) and the municipal waste (in thousand tons- as 'bad' output).

Then in order to test for the EKC hypothesis regional GDP per capita (GDPPC) has been used (€ per inhabitant). The data refer to NUTS 2 level[7] of 22 French, 39 German and 37 UK regions. In total our study constructs the REE indicators for ninety eight European regions. Table 1 presents the descriptive statistics of the variables used. As can be realized there are a lot of disparities among the ninety eight regions of our analysis.

Table 1: Descriptive statistics of the variables used

	Capital	*Labour*	*GDP*	*Regional Waste*	*GDPPC*
Mean	10170.98	965567.3	52202.85	1177.044	28217.35
Std	10660.18	689898.9	56816.25	1101.053	8363.298
Min	1546	104500	6133	205.36	18400
Max	90926	5416600	488428.4	9165.46	88300

[5] Available from: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/regional_statistics/data/main_tables
[6] Available from: http://stats.oecd.org/Index.aspx?DataSetCode=REG_LAB_TL3
[7] Details for regions at NUTS 2 level see:
for the UK: http://en.wikipedia.org/wiki/NUTS_of_the_United_Kingdom
for France: http://en.wikipedia.org/wiki/NUTS_of_France
for Germany: http://en.wikipedia.org/wiki/NUTS_of_Germany
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Following the notation by Färe and Grosskopf (2004) we let $P(x)$ to denote an input vector $x \in \Re_{+}^{N}$ which can produce a set of undesirable outputs $u \in \Re_{+}^{K}$ and of desirable outputs $y \in \Re_{+}^{M}$. Then in order to determine the environmental production several assumptions have to be taken into consideration (Shephard 1970; Shephard and Färe 1974; Färe and Primont 1995). We assume that the output sets are closed and bounded and that inputs are freely disposal. In addition $P(x)$ can be an environmental output set if:

$$(y,u) \in P(x) \text{ and } 0 \le \theta \le 1 \text{ then } (\theta y, \theta u) \in P(x) \tag{1}$$

(i.e. the outputs are weakly disposable) and

$$(y,u) \in P(x),\ u = 0 \text{ implies that } y = 0 \tag{2}$$

(i.e. the null jointness assumption of good and bad outputs).

The weak disposability assumption implies that the reduction of bad outputs is costly and therefore it can be obtained only by a simultaneously reduction of good outputs. In addition the assumption which indicates that the good outputs are null-joint with bad outputs implies that the bad outputs are byproducts of the production process when producing good outputs. In order to formalize the environmental technology we use the DEA framework.

Let $k = 1,...,K$ be the observations; then the environmental output can be formalized as:

$$\begin{aligned} P(x) = \Big\{ (y,u) : &\sum_{k=1}^{K} z_k y_{km} \ge y_m,\ m = 1,...,M, \\ &\sum_{k=1}^{K} z_k u_{kj} = u_j,\ j = 1,...,J, \\ &\sum_{k=1}^{K} z_k x_{kn} \le x_n,\ n = 1,...,N, \\ &z_k \ge 0, k = 1,...,K \Big\} \end{aligned} \tag{3}$$

Where $z_k,\ k=1,...,K$ indicate the intensity variables which are not negative and imply constant return to scale[8]. The inequality on the good outputs and the equality on the bad outputs will help us first to impose the weak disposability assumption on the bad outputs and secondly the strong disposability assumption on the good outputs. However the null-jointness is imposed by the following restrictions on bad outputs:

$$\begin{aligned} &\sum_{k=1}^{K} u_{kj} > 0, j = 1,...,J, \\ &\sum_{j=1}^{J} u_{kj} > 0, k = 1,...,K. \end{aligned} \tag{4}$$

Furthermore, we apply the directional distance function approach as in Chung et al. (1997) and in order to be able to reduce bad and expand good outputs. In order to be able to model that in the directional distance function setting we use a direction vector $g=\left(g_y,-g_u\right)$, where $g_y=1$ and $-g_u=-1$. Then the efficiency score for DMU k' can be obtained from:

$$\begin{aligned} &\vec{D}_o\left(x^{k'},y^{k'},u^{k'};g\right)=\max\beta \\ &s.t.\left(y^{k'}+\beta g_y,u^{k'}-\beta g_u\right)\in P\left(x\right) \end{aligned} \tag{5}$$

Next, the linear programming problem can be calculated as:

[8] Following Zelenyuk and Zheka (2006, p.149) our regional environmental efficiency measurement follows the most common assumption made in economics which is the constant returns to scale (CRS) assumption. In addition the CRS assumption enables us to obtain greater discriminative power, which in turn would result in larger variation of the regressand. Finally, due to the fact that we have a small sample size (98 regions) it is better in our analysis to use more robust scale assumptions. However, if the variable returns to scale is needed to be calculated the $\sum_{k=1}^{K} z_k = 1$ restriction must be added to the linear programming problem (3).

$$\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) = \max \beta$$

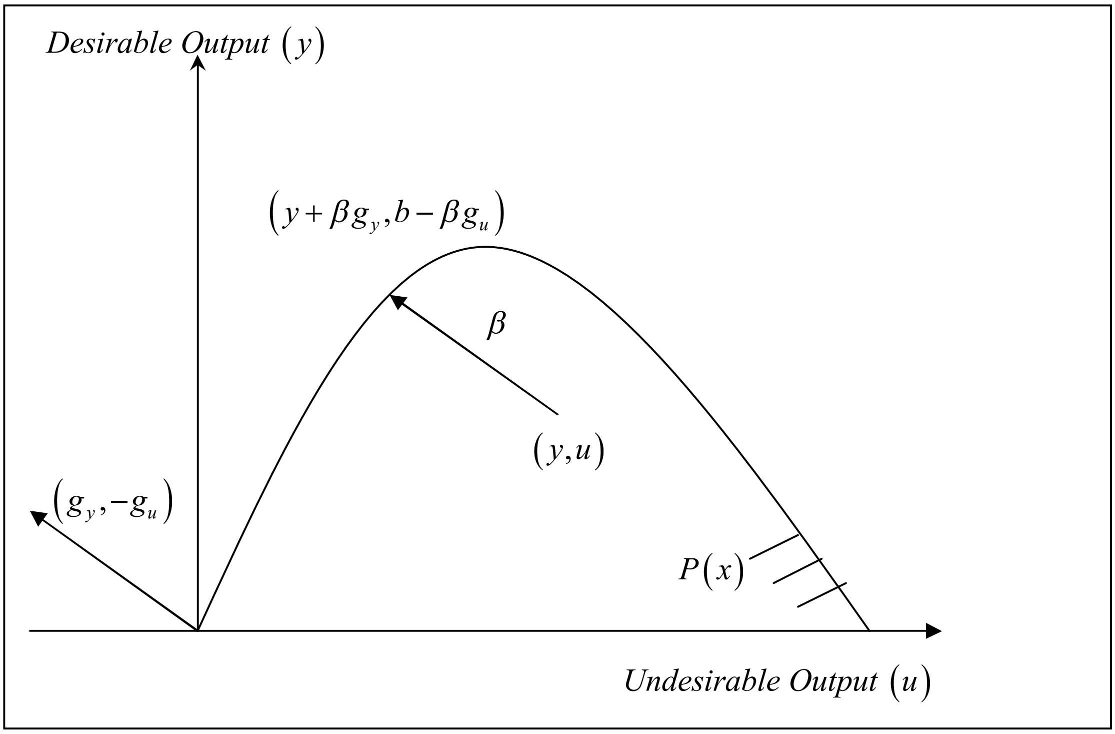
$$\begin{aligned} s.t. \quad & \sum_{k=1}^{K} z_k y_{km} \geq y_{k'm} + \beta g_{ym}, m = 1,\ldots,M, \\ & \sum_{k=1}^{K} z_k u_{kj} = u_{k'j} - \beta g_{uj}, j = 1,\ldots,J, \\ & \sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n} \\ & z_k \geq 0, k = 1,\ldots,K. \end{aligned} \tag{6}$$

A region is environmental efficient when $\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) = 0$ and environmental inefficient when $\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) > 0$. However in this study we transform the environmental efficiency scores in terms of Shephard's output distance function due to the fact that will be used to examine the effect of regional GDP per capita. Therefore, the environmental efficient region will be assigned with 1 and the environmental inefficiency will take values less than 1. In fact according to Chung et al. (1997) Shephard's output distance function is a special case of the directional distance function and can be calculated as:

$$D_o\left(x, y, u\right) = 1 / \left(1 + \vec{D}_o\left(x^k, y^k, u^k; y^k, u^k\right)\right) \tag{7}$$

Figure 1 illustrates the directional distance function for a case of one undesirable output and one desirable output for the regional environmental output set $P(x)$. The "null jointness" property described in (2) is diagrammatically represented because the function passes through the origin. The distance between a point (y, u) and the frontier $\left(y + \beta g_y, b - \beta g_u\right)$ is represented by the value of β. The direction vector $g = \left(g_y, -g_u\right)$ indicates the direction in which the regional environmental efficiency is measured with g_y indicating the direction of good output (in our case regional GDP) and with the direction vector g_u indicating the bad output (regional generation of municipality waste). Therefore given the regional environmental production technology $(P(x))$ and the specified direction vector (g), the directional distance function yields the contraction of regional waste and the maximum feasible expansion of regions' GDP.

Figure 1: Graphical presentation of the directional output distance function



In order to identify how regional GDP per capita (measured in €) used interrelates with the obtained regional environmental efficiency levels our paper constructs estimates of conditional stochastic kernel. Following, Racine (2008) let $f(.)$ and $\mu(.)$ be the joint and marginal densities of (X,Y) and X respectively. Let also Y and X be the dependent and independent variables accordingly $(Y = REE, X = GDPPC)$. Then the stochastic kernel (or the conditional distribution function) can be estimated as:

$$\hat{g}(y|x) = \hat{f}(x,y) / \hat{f}(x) \tag{8}$$

Using a product Gaussian kernel the $\hat{f}(x,y)$ can be estimated as:

$$\hat{f}(x,y) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{h_x\sqrt{2\pi}} e^{-0.5\left(\frac{X_i - x}{h_x}\right)^2} \frac{1}{h_y\sqrt{2\pi}} e^{-0.5\left(\frac{Y_i - y}{h_y}\right)^2} \tag{9}$$

and $\hat{f}(x)$ as: $$\hat{f}(x) = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{h_x\sqrt{2\pi}} e^{-0.5\left(\frac{X_i - x}{h_x}\right)^2} \tag{10}$$

where (h_x, h_y) are representing the bandwidths calculated by the least squares cross-validation data driven method as suggested by Hall et al. (2004)[9]. In addition the local constant estimator introduced from Nadaraya (1964) and Watson (1964) can be defined as:

$$\hat{g}(x) = \frac{\sum_{i=1}^{n} Y_i K\left(\frac{X_i - x}{h_x}\right)}{\sum_{i=1}^{n} K\left(\frac{X_i - x}{h_x}\right)} \tag{11}$$

In addition following the test proposed by Racine et al. (2006) and Racine (2008) we investigate the significance of regional GDPPC explaining the variations of regional REE. Specifically, if z denotes the explanatory variables that have be redundant from our model and X denotes the explanatory variable used (GDPPC in our case), then the null hypothesis can be written as $H_0 : E(y|x,z) = E(Y|z)$ almost everywhere .This can be equivalent to $H_0 : \frac{\partial E(y|x,z)}{\partial x} = \beta(x) = 0$ almost everywhere. Next the test statistic can be defined as:

[9] For empirical applications of conditional stochastic kernels on income dynamics see Fotopoulos (2009) and Poletti Laurini and Valls Pereira (2009).

$$I = E\left\{\beta(x)^2\right\} \tag{12}$$

In this way, the test statistic can be approximated as:

$$I_n = \frac{1}{n}\sum_{i=1}^{n}\hat{\beta}(X_i)^2 \tag{13}$$

and its distribution can be obtained by bootstrap procedures as described in Racine (1997).

4. Empirical Results

Following the methodology presented previously table 2 presents the environmental efficiency scores of the ninety eight regions shorted by country. The REE levels are taking values between 0 and 1 (1 indicating environmental efficient regions)[10]. As can be realized only six regions out of ninety eight are reported to be environmentally efficient regions. These are Inner London and North Eastern Scotland for the UK, Île de France and Corse for France and Hamburg and Rheinhessen-Pfalz two regions for Germany. In addition the six regions with the lowest environmental efficiency levels are reported to be Merseyside (0.638), Tees Valley and Durham (0.635), Cumbria (0.634), West Wales and The Valleys (0.625), Cornwall and Isles of Scilly (0.618) and Highlands and Islands (0.605).

When looking at the descriptive statistics the mean REE level of all the ninety eight regions is 0.749 with a standard deviation of 0.095. As has been presented in table 2, only thirty seven regions have been reported to have REE above the average value. When considering every country separately then different results can be reported. When observing the UK regions the five regions with the highest REE scores are reported to be Inner London, North Eastern Scotland, Berkshire, Buckinghamshire and Oxfordshire, Bedfordshire and Hertfordshire, Gloucestershire

[10] As reported previously the results are presented as Shephard's output distance measure following the transformation presented in equation (7).

and Wiltshire and Bristol/Bath area. In addition the five regions with lowest REE scores are reported to be Tees Valley and Durham, Cumbria, West Wales and The Valleys, Cornwall and Isles of Scilly and Highlands and Islands.

In the case of French regions the five regions with the highest REE levels are reported to be Île de France, Corse, Provence-Alpes-Côte d'Azur, Bretagne and Rhône-Alpes, whereas the regions with the lowest REE levels are Auvergne, Nord - Pas-de-Calais, Poitou-Charentes, Basse-Normandie and Bourgogne. Finally in the case of Germany the regions with the highest REE levels are reported to be Hamburg, Rheinhessen-Pfalz, Oberbayern, Bremen and Darmstadt whereas the regions with the lowest REE levels are Münster, Mecklenburg-Vorpommern, Trier, Sachsen-Anhalt and Lüneburg. The descriptive statistics of each country report that the UK regions have a mean REE value of 0.694, the French regions 0.732 and the German regions 0.816.

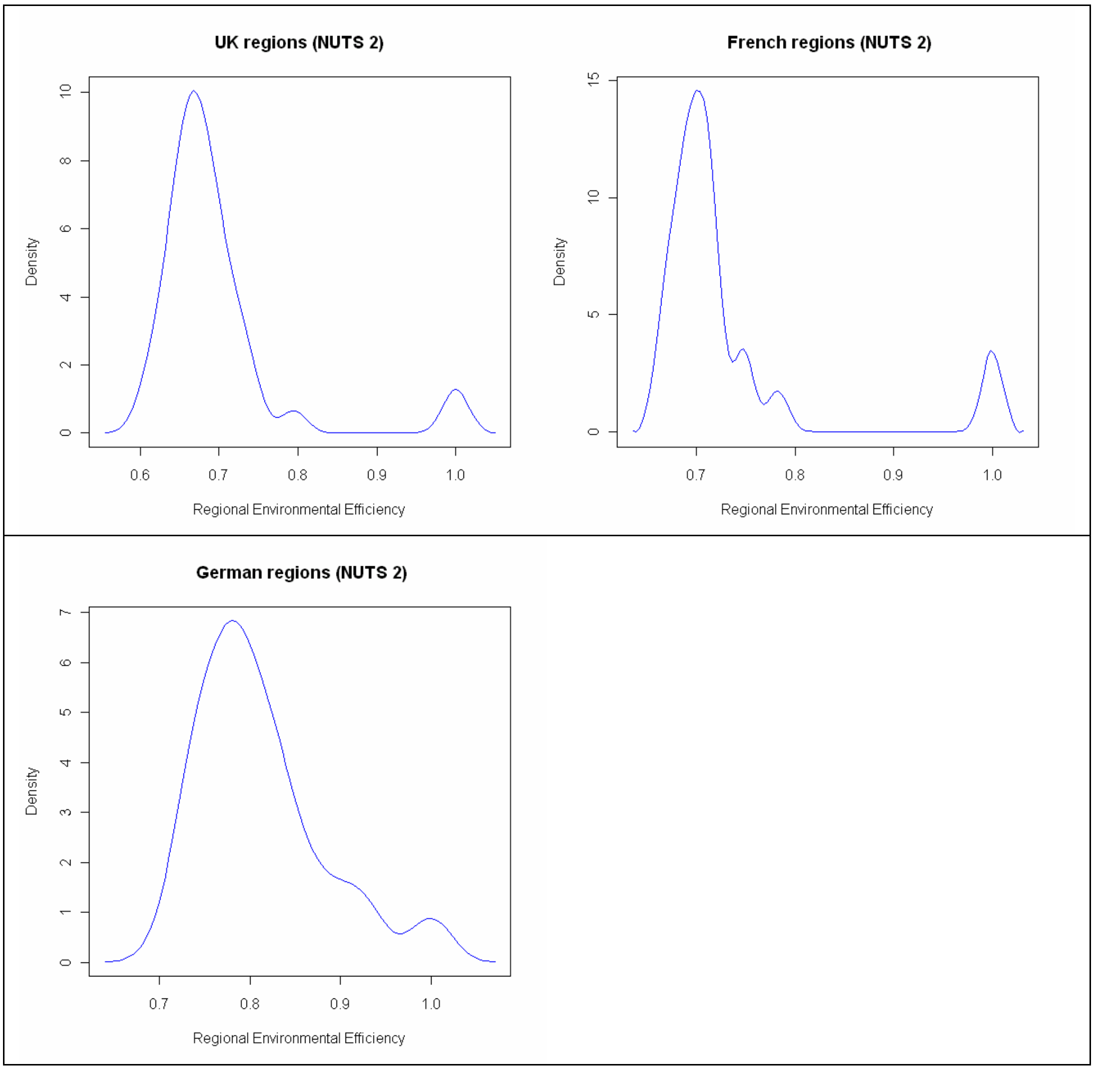
In addition to table 2, figure 2 provides the kernel density functions of countries' REE levels. For the calculation of the density estimates we have used the "normal reference rule-of-thumb" approach for bandwidth selection (Silverman 1986) and a second order Gaussian kernel. It appears that the highest probability of REE levels for Germany is about 0.8, for French regions about 0.7 and for the UK regions about 0.68. This result indicates that German regions tend to nave higher REE performance compared to French and UK regions. It also appears that the REE estimates for the UK and French regions are leptokurtic compared to the estimates for the German regions which appear to be platykurtic[11].

[11] The leptokurtic distributions indicate that there is a rapid fall-off in the density as we move away from the mean. Furthermore, the pickedness of the distribution suggests a clustering around the mean with rapid fall around it.

Table 2: Estimated regional environmental efficiency (REE) levels

UK regions (37)	REE	French regions (22)	REE	German regions (39)	REE
Tees Valley and Durham	0.635	*Île de France*	1.000	*Stuttgart*	0.882
Northumberland and Tyne and Wear	0.668	*Champagne-Ardenne*	0.711	*Karlsruhe*	0.848
Cumbria	0.634	*Picardie*	0.691	*Freiburg*	0.805
Cheshire	0.712	*Haute-Normandie*	0.713	*Tübingen*	0.883
Greater Manchester	0.694	*Centre (FR)*	0.687	*Oberbayern*	0.929
Lancashire	0.663	*Basse-Normandie*	0.667	*Niederbayern*	0.796
Merseyside	0.638	*Bourgogne*	0.667	*Oberpfalz*	0.831
East Yorkshire and Northern Lincolnshire	0.651	*Nord - Pas-de-Calais*	0.680	*Oberfranken*	0.772
North Yorkshire	0.660	*Lorraine*	0.698	*Mittelfranken*	0.836
South Yorkshire	0.670	*Alsace*	0.708	*Unterfranken*	0.788
West Yorkshire	0.702	*Franche-Comté*	0.701	*Schwaben*	0.827
Derbyshire and Nottinghamshire	0.682	*Pays de la Loire*	0.695	*Berlin*	0.783
Leicestershire, Rutland and Northamptonshire	0.695	*Bretagne*	0.748	*Brandenburg - Nordost*	0.759
Lincolnshire	0.648	*Poitou-Charentes*	0.674	*Brandenburg - Südwest*	0.773
Herefordshire, Worcestershire and Warwickshire	0.677	*Aquitaine*	0.714	*Bremen*	0.927
Shropshire and Staffordshire	0.654	*Midi-Pyrénées*	0.695	*Hamburg*	1.000
West Midlands	0.696	*Limousin*	0.714	*Darmstadt*	0.910
East Anglia	0.692	*Rhône-Alpes*	0.747	*Gießen*	0.787
Bedfordshire and Hertfordshire	0.739	*Auvergne*	0.685	*Kassel*	0.795
Essex	0.679	*Languedoc-Roussillon*	0.718	*Mecklenburg-Vorpommern*	0.737
Inner London	1.000	*Provence-Alpes-Côte d'Azur*	0.783	*Braunschweig*	0.782
Outer London	0.728	*Corse*	1.000	*Hannover*	0.747
Berkshire, Buckinghamshire and Oxfordshire	0.795			*Lüneburg*	0.711
Surrey, East and West Sussex	0.717			*Weser-Ems*	0.743
Hampshire and Isle of Wight	0.713			*Düsseldorf*	0.821
Kent	0.673			*Köln*	0.788
Gloucestershire, Wiltshire and Bristol/Bath area	0.738			*Münster*	0.738
Dorset and Somerset	0.666			*Detmold*	0.859
Cornwall and Isles of Scilly	0.618			*Arnsberg*	0.797
Devon	0.651			*Koblenz*	0.744
West Wales and The Valleys	0.625			*Trier*	0.735
East Wales	0.684			*Rheinhessen-Pfalz*	1.000
Eastern Scotland	0.674			*Saarland*	0.776
South Western Scotland	0.662			*Chemnitz*	0.809
North Eastern Scotland	1.000			*Dresden*	0.826
Highlands and Islands	0.605			*Leipzig*	0.834
Northern Ireland (UK)	0.651			*Sachsen-Anhalt*	0.733
				Schleswig-Holstein	0.759
				Thüringen	0.764
Mean	0.694	*Mean*	0.732	*Mean*	0.814
Std	0.083	*Std*	0.091	*Std*	0.071
Min	0.605	*Min*	0.667	*Min*	0.711
Max	1.000	*Max*	1.000	*Max*	1.000
Despriptive statistics of all regions (98)					
Mean	0.749				
Std	0.095				
Min	0.605				
Max	1.000				

Figure 2: Kernel density functions of regions' environmental efficiencies using Gaussian Kernel



As a further step in our analysis figure 3 presents the conditional stochastic kernel between REE and regional per capita GDP (GDPPC) in order to analyze how per capita regional economic levels affect regions' environmental efficiencies[12]. In order to understand figure 3 a fixed point can be chosen on the axis labeled REE. Then, by slicing the graph from this point and moving parallel to GDPPC axis, the estimated distribution of regions' environmental efficiency levels over the examined time period conditional on GDPPC levels can be traced. The graphic shows that regions in the extremes of environmental efficiency have higher probability

[12] According to Li and Racine (2007) nonparametric approaches can reveal structure in the data which might be missed when applying common parametric functional specifications.

generated by the respective extremes of per capita growth levels, i.e., low-environmental efficiency regions have high probability to have been generated by lower GDP per capita levels and high-environmental efficiency regions, by higher GDP per capita levels.

However, for the intermediate-environmental efficient regions (with REE between 0.7-0.85), the effect of per capita GDP is less determinant, given the high dispersion of estimated densities. We can interpret this result as regional club convergence (which is conditioned on GDPPC)[13]. In addition and in order to test for the EKC hypothesis we applied nonparametric regression of regional GDPPC and REE levels. As such figure 4 illustrates the nonparametric estimate of the regression function between regional GDPPC and REE alongside with their variability bounds of pointwise error bars using asymptotic standard error formulas (Hayfield and Racine 2008)[14].

Following the significance test described previously (equations 12, 13) we obtained a p-value of 0.0426 (which is significant at 5% level) indicating that regional GDPPC can explain the variations of REE levels among the regions. As can been observed from figure 3 regional GDPPC has a clear positive effect on regions' environmental efficiency levels. As regional per capita GDP levels increasing, then regions' environmental efficiency levels are also increasing monotonically[15].

[13] In fact regardless their GDP per capita levels fifty (out of ninety eight) regions have environmental efficiency levels between 0.7-0.85.

[14] One environmental efficient region (Inner London with efficiency score equal to 1) has been excluded from the analysis because it has significantly higher GDP per capita levels (88300) compared to the other regions and acts as an outlier. This in turn masks the visualisation effect obtained from the conditional stochastic kernel and the nonparametric regression analysis and therefore it may provide us with misleading results.

[15] As such the EKC hypothesis is not verified in our case.

Our results compliment the studies by Grossman and Kruger (1991), Hettige et al. (1992) which found that in regional level pollutants tend to decrease with increasing per capita income. Similarly, our results support the findings by Carson et al. (1997) indicating that high-income states have low per capita emissions while emissions in lower-income states are highly variable (p. 447).

Figure 3*:* Conditional stochastic kernels for the 98 regions considered (REE conditioned on regional GDP per capita (GDPPC) levels)

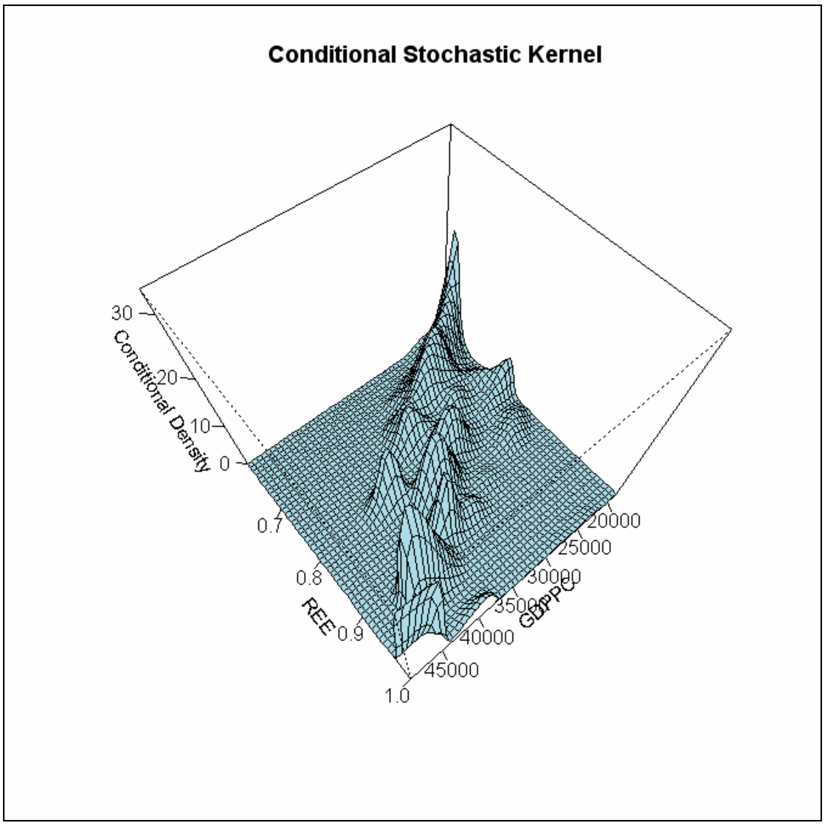
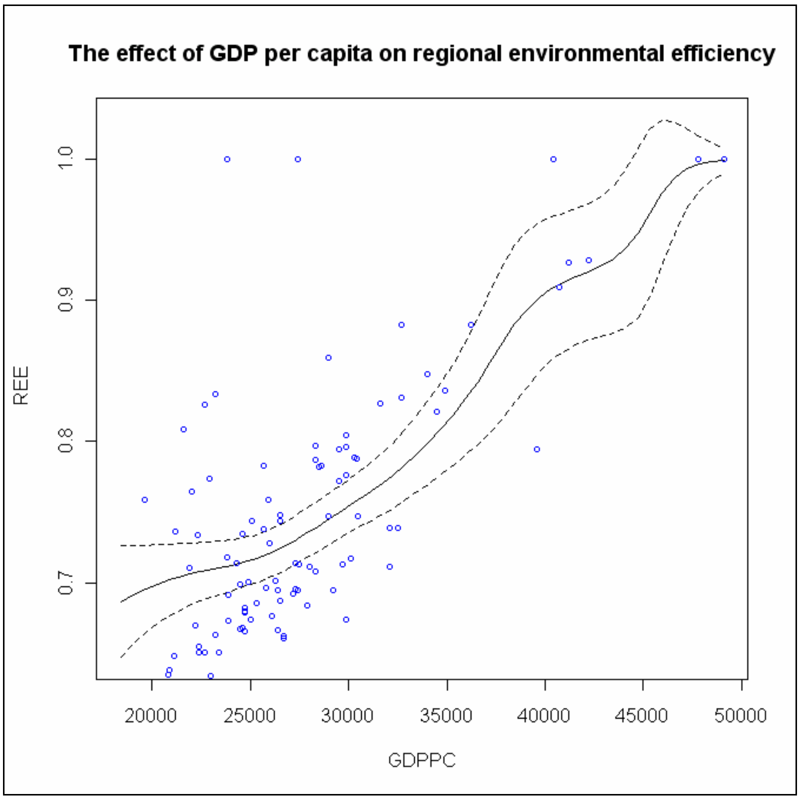


Figure 4: The effect of per capita regional GDP on regions' environmental efficiency



5. Conclusions

Our paper by applying directional distance function approach and the property of weak disposability measures spatial environmental heterogeneities of ninety eight European regions (NUTS 2 level). The results clearly demonstrate that there are a lot of environmental inefficiencies among the regions. In addition by applying stochastic kernels and the local constant estimator, the paper examines the effect of regional GDP per capita on the obtained regional environmental efficiency levels in order to verify the EKC hypothesis. The results reveal that there is a strong monotonic positive relationship between high regional environmental efficiency and regional economic growth. In addition the results couldn't provide evidence of the EKC hypothesis.

The contribution of the paper is twofold: first and with respect to the methodologies applied, it illustrates how the environmental quality-economic activity relationship can be examined in a regional level. Secondly, given the need for studies examined such a relationship in a regional level; our paper contributes to the existence literature by providing for the first time empirical evidence for ninety eight regions from Germany, France and the UK.

However it is worth mentioning that given the contribution of the paper, a potential weakness concerns the lack of regional data (the analysis was carried out only for 2005). Nevertheless, the evidence provided through the present nonparametric analysis clearly supports the empirical results of other studies (like Bockstael 1996; Goodchild et al. 2000; Anselin 2001) suggesting that the environmental quality-economic growth relationship provides different results when the spatial dimension is taken into account which in turn can affect regional environmental policies planning and implementation.

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