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**Abstract**

This paper by applying a directional distance function approach measures the UK regions' municipality waste performance. In addition the paper constructs conditional stochastic kernels trying to determine nonparametrically the association of regions' GDP per capita levels with their calculated regional environmental efficiencies. There are evidences of regional environmental inefficiencies for the majority of UK regions regardless their regional GDP per capita levels.

**Keywords:** Regional environmental performance; Directional distance function; Conditional stochastic kernel

**JEL classification:** C6, O13, Q5.

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## 1. Introduction

The measurement of environmental technology has been an open challenge for researchers. The problem lies on the treatment of the pollutant[1] in production function framework. One of the ways that the ‘bad’ output can be modelled appeared in the pioneered work by Färe *et al.* (1989) by assuming 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). 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, Kuosmanen, 2005; Färe and Grosskopf, 2009; Kuosmanen and Podinovski, 2009).

Our study applies the weak disposability assumption in a directional distance function measure in order to determine for the first time the environmental performance of UK regions.

## 2. Data and Methodology

In our analysis we use data collected we use data collected from two different regional databases (Eurostat[2] and OECD[3]) and concerning the year 2005. The two inputs used in our analysis are total regional labour force and regional gross fixed capital formation (in million Euros). In addition the two outputs used in our study are regional gross domestic product (million PPS- good output) and as ‘bad’ output

[1] The pollutant is also referred to the literature of measuring environmental technology as ‘bad’ output.
[2] Available from: http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/introduction
[3] Available from: http://stats.oecd.org/Index.aspx?DataSetCode=REG_LAB_TL3

municipal waste (in 1000t). The data are referring to NUTS 2 level of the UK regions[4].

Therefore, following 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 desirable outputs $y \in \Re_{+}^{M}$. Then in order to determine the environmental technology several assumptions are needed to be taken following Shephard (1970), Shephard and Färe (1974) and 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:

1. $(y,u) \in P(x)$ and $0 \le \theta \le 1$ then $(\theta y, \theta u) \in P(x)$ (i.e. the outputs are weakly disposable) and

2. $(y,u) \in P(x)$, $u = 0$ implies that $y = 0$ (i.e. the null jointness assumption of good and bad outputs).

The weak disposability assumption implies that the reduction of bad outputs are costly and therefore the reduction of bad outputs can be obtained only by a simultaneous 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 efficiency we use data envelopment analysis (DEA) framework. Let $k = 1,...,K$ be the observations and then the environmental output can be formalized as:

[4] For information regarding UK's regions see: http://en.wikipedia.org/wiki/NUTS_of_the_United_Kingdom

$$P(x)=\Big\{(y,u):\sum_{k=1}^{K} z_k y_{km} \geq y_m, m=1,...,M,$$

$$\sum_{k=1}^{K} z_k u_{kj} = u_j, j=1,...,J, \tag{1}$$

$$\sum_{k=1}^{K} z_k x_{kn} \leq x_n, n=1,...,N,$$

$$z_k \geq 0, k=1,...,K\Big\}$$

$z_k, k=1,...,K$ indicate the intensity variables which are not negative and imply constant return to scale[5]. The inequality on the good outputs and the equality on the bad outputs help us to impose the weak disposability assumption and only strong disposability of good outputs. However the null-jointness is imposed by the following restrictions on bad outputs:

$$\sum_{k=1}^{K} u_{kj} > 0, j=1,...,J,$$
$$\sum_{j=1}^{J} u_{kj} > 0, k=1,...,K. \tag{2}$$

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 $g=(g_y,-g_u)$, where $g_y=1$ and $-g_u=-1$. Then the efficiency score for a region $k'$ can be obtained from:

$$\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) = \max \beta$$
$$s.t.\left(y^{k'}+\beta g_y, u^{k'}-\beta g_u\right) \in P(x) \tag{3}$$

then the linear programming problem can be calculated as:

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[5] 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 provides as with greater discriminative power among the examined regions. Finally, due to the fact that we have a small sample size (37 regions) it is therefore better for our analysis to use more robust scale assumptions. However, if the variable returns are needed to be calculated the $\sum_{k=1}^{K} z_k = 1$ restriction must be added to the linear programming problem (1).

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

$$\begin{aligned} s.t. \quad & \sum_{k=1}^{K} z_k y_{km} \geq y_{k'm} + \beta g_{ym}, m = 1,...,M, \\ & \sum_{k=1}^{K} z_k u_{kj} = u_{k'j} - \beta g_{uj}, j = 1,...,J, \\ & \sum_{k=1}^{K} z_k x_{kn} \leq x_{k'n} \\ & z_k \geq 0, k = 1,...,K. \end{aligned} \qquad (4).$$

Efficiency is afterward indicated when $\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) = 0$ and inefficiency when $\vec{D}_o\left(x^{k'}, y^{k'}, u^{k'}; g\right) > 0$. Due to the fact that we are using the efficiency scores obtained in a second stage analysis we present the efficiency scores obtained in terms of Shephard's output distance function. 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:

$$D_o\left(x, y, u\right) = 1 / \left(1 + \vec{D}_o\left(x^k, y^k, u^k; y^k, u^k\right)\right) \qquad (5).$$

In addition this paper constructs estimates of conditional stochastic kernel and in order to identify how regional GDP per capita (GDPPC) used interrelates with the obtained regional environmental efficiency (REE) levels[6]. Following, Racine (2008) let $f(.)$ and $\mu(.)$ be the joint and marginal densities of $(X, Y)$ and $X$ respectively. Let $Y$ and $X$ be the dependent and independent variables accordingly $(Y = REE, X = GDPPC)$. Then the stochastic kernel (or the conditional

[6] From the analysis have been excluded the two environmental efficient regions (i.e. Inner London and North Eastern Scotland, with efficiency score equal to 1) because they have significantly higher GDP per capita levels (88300 and 40400 euros) compared to the other regions. This in turn masks the visualisation effect obtained from the conditional stochastic kernel and can provide us with misleading results.

distribution function) can be estimated as:

$$\hat{g}\left(y|x\right)=\hat{f}\left(x,y\right)/\hat{f}\left(x\right) \qquad (6).$$

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

$$\hat{f}\left(x,y\right)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2}\frac{1}{h_y\sqrt{2\pi}}e^{-0.5\left(\frac{y-y_i}{h_y}\right)^2} \qquad (7)$$

and $\hat{f}\left(x\right)$ as:

$$\hat{f}\left(x\right)=\frac{1}{n}\sum_{i=1}^{n}\frac{1}{h_x\sqrt{2\pi}}e^{-0.5\left(\frac{x-x_i}{h_x}\right)^2} \qquad (8)$$

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)[7].

## 3. Empirical Results and Conclusions

The empirical results (Table1) indicate that Inner London and North Eastern Scotland appear to be environmental efficient regions. In addition the last fiveUK regions in terms of the lowest environmental efficiencies are reported to be Tees Valley and Durham, Cumbria, West Wales and The Valleys, Cornwall and Isles of Scilly and Highlands and Islands. In addition Table 1 indicates that the average REE level is 0.7 (with standard deviation equals to 0.09). As it can be observed only fourteen UK regions are reported to have REE score above 0.7. These are reported to be Inner London, North Eastern Scotland, Berkshire, Buckinghamshire and Oxfordshire, Bedfordshire and Hertfordshire, Gloucestershire, Wiltshire and Bristol/Bath area, Outer London, Surrey, East and West Sussex, Hampshire and Isle of Wight, Cheshire, West Yorkshire, West Midlands, Leicestershire, Rutland and Northamptonshire, Greater Manchester and East Anglia.

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

*Table 1: UK regions' environmental efficiency levels measured in Shephard's output distance functions*

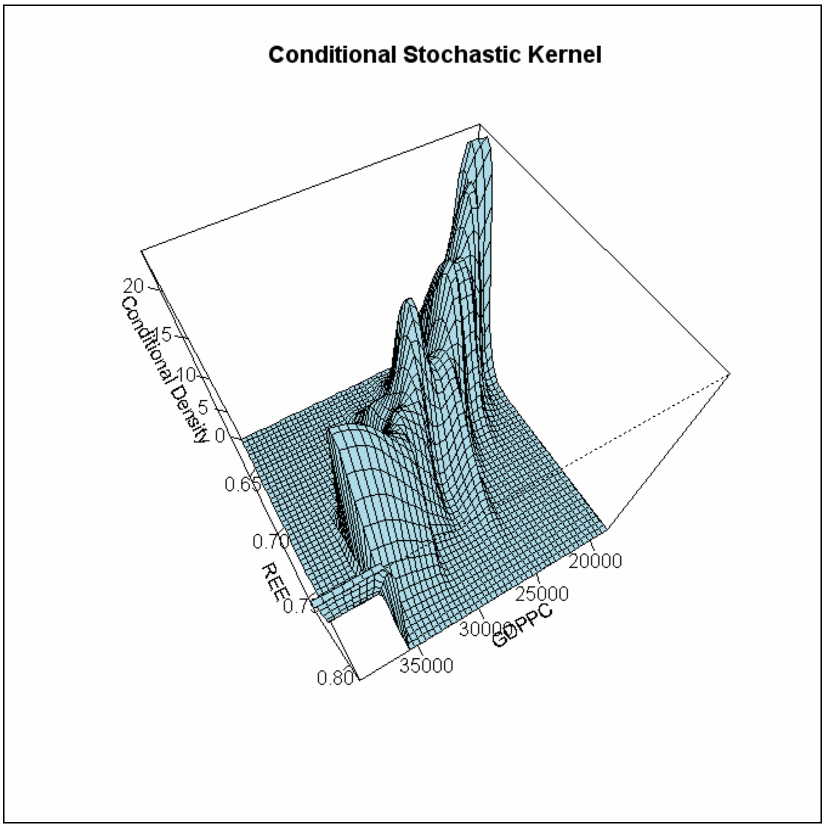
| UK Regions-NUTS2 | *REE* | UK Regions-NUTS2 | *REE* |
|---|---|---|---|
| Tees Valley and Durham | 0.6423 | Essex | 0.6891 |
| Northumberland and Tyne and Wear | 0.6776 | Inner London | 1.0000 |
| Cumbria | 0.6418 | Outer London | 0.7409 |
| Cheshire | 0.7236 | Berkshire, Buckinghamshire and Oxfordshire | 0.8114 |
| Greater Manchester | 0.7053 | Surrey, East and West Sussex | 0.7296 |
| Lancashire | 0.6719 | Hampshire and Isle of Wight | 0.7249 |
| Merseyside | 0.6458 | Kent | 0.6829 |
| East Yorkshire and Northern Lincolnshire | 0.6591 | Gloucestershire, Wiltshire and Bristol/Bath area | 0.7520 |
| North Yorkshire | 0.6694 | Dorset and Somerset | 0.6749 |
| South Yorkshire | 0.6794 | Cornwall and Isles of Scilly | 0.6243 |
| West Yorkshire | 0.7130 | Devon | 0.6593 |
| Derbyshire and Nottinghamshire | 0.6925 | West Wales and The Valleys | 0.6319 |
| Leicestershire, Rutland and Northamptonshire | 0.7057 | East Wales | 0.6942 |
| Lincolnshire | 0.6563 | Eastern Scotland | 0.6835 |
| Herefordshire, Worcestershire and Warwickshire | 0.6867 | South Western Scotland | 0.6714 |
| Shropshire and Staffordshire | 0.6631 | North Eastern Scotland | 1.0000 |
| West Midlands | 0.7074 | Highlands and Islands | 0.6230 |
| East Anglia | 0.7027 | Northern Ireland (UK) | 0.6593 |
| Bedfordshire and Hertfordshire | 0.7526 | | |
| ***Mean*** | | | ***0.7040*** |
| ***Std*** | | | ***0.0817*** |
| ***Min*** | | | ***0.6230*** |
| ***Max*** | | | ***1.0000*** |

Furthermore, and in order to understand how per capita regional income levels affect regions environmental efficiencies we construct conditional stochastic kernels between REE and GDPPC variables[8]. This relationship is presented on Figure 1 in a conditional stochastic kernel form. When looking Figure 1 we can choose a fixed point on the axis labeled REE and then by slicing the graph from this point and moving parallel to GDPPC axis, the estimated distribution of regions' REE 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 which have been generated by the respective extremes of per capita

[8] The routes and theory behind the link of environmental quality and economic development stages, income disparities can be found in the works of Kuznets (1955), Grossman and Kruger (1995) and Dasgupta et al. (2002).

growth levels. That is low-environmental efficiency regions have high probability that 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 0.65-0.70), the effect of per capita income is less determinant, given the high dispersion of estimated densities. We can interpret this result as club convergence (which is conditioned on GDPPC)[9].

***Figure 1: Conditional stochastic kernels of UK regions-Regional environmental efficiency (REE) conditioned on regional GDP per capita (GDPPC) levels***




Finally, in respect to the methodologies adopted the contribution of the paper is twofold: to demonstrate how directional distance functions can be applied in a regional level and how then the estimation of conditional stochastic kernels can be

[9] In fact regardless their GDP per capita levels twenty one (out of thirty seven) UK regions have environmental efficiency levels between 0.65-0.7.

used in order to examine the regional environmental quality-economic growth relationship.

## References

Chung Y.H., Färe R., Grosskopf S., 1997. Productivity and undesirable outputs: A directional distance function approach. Journal of Environmental Management 51, 229– 240.

Dasgupta S., Laplante B., Wang H., Wheeler D. 2002. Confronting the Environmental Kuznets Curve. Journal of Economic Perspectives 16, 147– 168.

Färe R., Grosskopf S., Tyteca D. 1996. An activity analysis model of the environment performance of firms: application to fossil-fuel-fired electric utilities. Ecological Economics 18, 161–175.

Färe R., Grosskopf S. 2003. Non-parametric Productivity Analysis with Undesirable Outputs: Comment. American Journal of Agricultural Economics 85, 1070–74.

Färe R., Grosskopf S. 2009. A Comment on Weak Disposability in Nonparametric Production Analysis. American Journal of Agricultural Economics 91, 535-538.

Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C., 1989. Multilateral productivity comparisons when some outputs are undesirable. The Review of Economics and Statistics 71, 90–98.

Färe R., Primont D. 1995. Multi-Output Production and Duality: Theory and Applications. Kluwer Academic Publishers, Boston.

Färe R., Grosskopf S. 2004. Modeling undesirable factors in efficiency evaluation: Comment. European Journal of Operational Research 157, 242-245.

Fotopoulos G. 2006. Nonparametric analysis of regional income dynamics: The case of Greece. Economics Letters 91, 450-457.

Grossman G.M., Krueger A.B. (1995) Economic growth and the environment. The Quarterly Journal of Economics 110, 353-377.

Hailu A. 2003. Non-parametric Productivity Analysis with Undesirable Outputs: Reply. American Journal of Agricultural Economics 85, 1075–77.

Hailu A., Veeman TS. 2001. Non-parametric Productivity Analysis with Undesirable Outputs: An Application to the Canadian Pulp and Paper Industry. American Journal of Agricultural Economics 83, 605–16.

Hall P., Racine J.S., Li Q. 2004. Cross-validation and the estimation of conditional probability densities. Journal of the American Statistical Association 99, 1015–1026.

Kuosmanen T. 2005. Weak disposability in nonparametric production analysis with undesirable outputs. American Journal of Agricultural Economics 87, 1077-1082.

Kuosmanen T., Podinovski V. 2009. Weak disposability in nonparametric production analysis: reply to Färe and Grosskopf. American Journal of Agricultural Economics 91, 539-545.

Kuznets S. 1955. Economic growth and income inequality. American Economic Review 45, 1-28.

Poletti Laurini M., Valls Pereira P.L. 2009. Conditional stochastic kernel estimation by nonparametric methods. Economics Letters 105, 234-238.

Racine J.S. 2008. Nonparametric Econometrics: A Primer. Found and Trends Econometrics 3, 1-88.

Shephard R.W. 1970. Theory of Cost and Production Functions. Princeton University Press, Princeton, NJ.

Shephard R.W., Färe R. 1974. The law of diminishing returns. Zeitschrift für Nationalökonomie 34, 60–90.

Tyteca D. 1996. On the Measurement of the Environmental Performance of Firms- A Literature Review and a Productive Efficiency Perspective. Journal of Environmental Management 46, 281- 308.

Tyteca D. 1997. Linear programming models for the measurement of environmental performance of firms: concepts and empirical results. Journal of Productivity Analysis 8, 175–189.

Zelenyuk V., Zheka V. 2006. Corporate governance and firm's efficiency: the case of a transitional country, Ukraine. Journal of Productivity Analysis 25, 143-157.

Zofio J.L., Prieto A.M. 2001. Environmental efficiency and regulatory standards: the case of CO2 emissions from OECD industries. Resource and Energy Economics 23, 63–83.