Economics Letters 120 (2013) 48–52

Contents lists available at SciVerse ScienceDirect

Economics Letters

journal homepage: www.elsevier.com/locate/ecolet

Economic growth and environmental efficiency: Evidence from US regions

George E. Halkos *, Nickolaos G. Tzeremes

Laboratory of Operations Research, Department of Economics, University of Thessaly, Korai 43, 38333, Volos, Greece

HIGHLIGHTS

- A conditional directional distance function model is proposed.
- Exogenous factors for measuring environmental efficiency are incorporated.
- Our proposed model is applied in the US regions' environmental efficiency.
- We find that under the effect of regional GDP/c environmental efficiency decreases.
- The examined relationship has an inverted "U" shape form.

ARTICLE INFO

Article history:
Received 18 November 2012
Received in revised form
18 January 2013
Accepted 24 March 2013
Available online 29 March 2013

JEL classification:
C14
Q50
R11

Keywords:
Regional environmental efficiency
Directional distance function
Conditional measures
US regions

ABSTRACT

This paper proposes a conditional directional distance function estimator in order to examine the link between regional environmental efficiency and GDP per capita levels. As an illustrative example we apply our model to US regional data revealing an inverted 'U' shape relationship between regional environmental efficiency and per capita income. The results derived from a non-parametric regression indicate a turning point at 49,000 dollars.

1. Introduction

Recently, Simar and Vanhems (2012) introduced directional distance functions conditioned to exogenous (environmental) factors. The proposed formulation incorporates into the efficiency measurement an exogenous factor that may influence the production process. This note applies the methodology of conditional directional distance functions into an environmental problem, in order to analyze the impact of economic growth on regional environmental efficiency for the case of the US regions.

Specifically, our paper extends the estimator originated by Kuosmanen (2005) measuring environmental efficiency. The modified version is based on conditional directional distance functions incorporating the effect of exogenous factors. In our empirical application our proposed estimator examines the effect of regional economic growth on 51 US regions' environmental efficiency levels.

2. Methodology

Following several authors (Kuosmanen, 2005; Kuosmanen and Podinovski, 2009; Podinovski and Kuosmanen, 2011; Kuosmanen and Matin, 2011) a vector $\mathbf{v} = (v_1, \ldots, v_M) \in \Re_+^M$ indicates the desirable (or good) outputs, a vector $\mathbf{w} = (w_1, \ldots, w_J) \in \Re_+^J$ the undesirable (or bad) outputs and a vector $\mathbf{x} = (x_1, \ldots, x_N) \in \Re_+^N$ the inputs used. The production technology can then be characterized by the production set as:

$$\mathbf{Y} = \{(\mathbf{v}, \mathbf{w}, \mathbf{x}) | \mathbf{x} \text{ can produce } (\mathbf{v}, \mathbf{w})\}. \quad (1)$$

Moreover we assume that the production technology satisfies the following three axioms:

* Corresponding author. Tel.: +30 24210 74920; fax: +30 24210 74772.
E-mail address: halkos@econ.uth.gr (G.E. Halkos).
URL: http://www.halkos.gr/ (G.E. Halkos).

0165-1765/$ – see front matter © 2013 Elsevier B.V. All rights reserved.
http://dx.doi.org/10.1016/j.econlet.2013.03.043

(A1) *Convexity*. Technology $\mathbf{Y}$ is convex.
(A2) *Strong disposability of inputs and good outputs*. If $(\mathbf{v}, \mathbf{w}, \mathbf{x}) \in \mathbf{Y}$, $0 \le \mathbf{v}' \le \mathbf{v}$ and $\mathbf{x}' \ge \mathbf{x}$ then $(\mathbf{v}', \mathbf{w}, \mathbf{x}') \in \mathbf{Y}$.
(A3) *Weak disposability of all outputs*. If $(\mathbf{v}, \mathbf{w}, \mathbf{x}) \in \mathbf{Y}$ and $\theta \in [0, 1]$ then $(\theta\mathbf{v}, \theta\mathbf{w}, \mathbf{x}) \in \mathbf{Y}$.

The weak disposability axiom (A3) implies that if input $\mathbf{x}$ can produce $(\mathbf{v}, \mathbf{w})$ then it is possible to decrease the vector of undesirable outputs[1] by a uniform factor "θ".[2] However as Kuosmanen (2005) proved that a uniform abatement factor underestimates the production possibilities under the stated assumptions. Therefore, having k regions under consideration and the observed activities defined as $(\mathbf{v}^k, \mathbf{w}^k, \mathbf{x}^k)$, $k = 1, \dots, K$, we can allow for non-uniform abatement factors across the regions (indicated by "θ^k") following Kuosmanen's estimator in the context of data envelopment analysis (DEA) terminology:

$$\hat{\mathbf{Y}} = \left\{ (\mathbf{v}, \mathbf{w}, \mathbf{x}) : \begin{array}{l} \sum_{k=1}^{K} \theta^k \omega^k v_m^k \ge v_m, \ \forall m \\ \sum_{k=1}^{K} \theta^k \omega^k w_j^k = w_j, \ \forall j \\ \sum_{k=1}^{K} \omega^k x_n^k \le x_n, \ \forall n \\ \sum_{k=1}^{K} \omega^k = 1 \\ \omega^k \ge 0, \ \forall k \\ 0 \le \theta^k \le 1, \ \forall k \end{array} \right\} \tag{2}$$

where variables $\boldsymbol{\omega} = (\omega^1, \dots, \omega^k)$ are referred to as the intensity weights. However formulation (2) is nonlinear and in order to be linearized we can use the following substitutions:

$$\lambda^k = \theta^k \omega^k, \qquad \mu^k = (1 - \theta^k)\omega^k, \quad \forall k, \ \text{so that } \lambda^k + \mu^k = \omega^k. \tag{3}$$

Finally, the linearized form of (2) modeling weak disposability with non-uniform factors can be expressed as:

$$\hat{\mathbf{Y}} = \left\{ (\mathbf{v}, \mathbf{w}, \mathbf{x}) : \begin{array}{l} \sum_{k=1}^{K} \lambda^k v_m^k \ge v_m, \forall m \\ \sum_{k=1}^{K} \lambda^k w_j^k = w_j, \forall j \\ \sum_{k=1}^{K} \left(\lambda^k + \mu^k\right) x_n^k \le \left(\lambda^k + \mu^k\right) x_n, \forall n \\ \sum_{k=1}^{K} \left(\lambda^k + \mu^k\right) = 1 \\ \lambda^k, \mu^k \ge 0, \forall k \end{array} \right\}. \tag{4}$$

For given activity of a region $(\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0)$ the output directional distance function allowing a simultaneous increase in good and a reduction of bad output (Chambers et al., 1998; Chung et al., 1997) can be defined as:

$$D(\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w) = \sup\{\phi | (\mathbf{v}^0 + \phi\mathbf{g}^v, \mathbf{w}^0 - \phi\mathbf{g}^w, \mathbf{x}^0) \in \mathbf{Y}\}. \tag{5}$$

Then, the linear program calculating regions' output directional distance function under the Kuosmanen (2005) technology can be defined as:

$$\hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w) = \max \phi$$

$$\text{Subject to} \quad \begin{array}{l} \sum_{k=1}^{K} \lambda^k v_m^k \ge v_m^0 + \phi g_m^v, \quad \forall m \\ \sum_{k=1}^{K} \lambda^k w_j^k = w_j^0 - \phi g_j^w, \quad \forall j \\ \sum_{k=1}^{K} \left(\lambda^k + \mu^k\right) x_n^k \le \left(\lambda^k + \mu^k\right) x_n^0, \quad \forall n \\ \sum_{k=1}^{K} \left(\lambda^k + \mu^k\right) = 1 \\ \lambda^k, \quad \mu^k \ge 0, \quad \forall k. \end{array} \tag{6}$$

Daraio and Simar (2005) extended the probabilistic formulation of the production process first introduced by Cazals et al. (2002).[3] In our proposed setting we define the joint probability measure of our environmental production $(\mathbf{v}, \mathbf{w}, \mathbf{x})$ and the joint probability function of $H_{\mathbf{v},\mathbf{w},\mathbf{x}}(\cdot, \cdot)$ as:

$$H_{\mathbf{v},\mathbf{w},\mathbf{x}}(x, v, w) = \text{Prob}(\mathbf{x} \le x, \mathbf{v} \ge v, \mathbf{w} \ge w). \tag{7}$$

Then the following decomposition can be obtained:

$$\begin{aligned} H_{\mathbf{v},\mathbf{w}}(x, v, w) &= \text{Prob}(\mathbf{v} \ge v, \mathbf{w} \ge w | \mathbf{x} \le x)\text{Prob}(\mathbf{x} \le x) \\ &= S_{\mathbf{v},\mathbf{w}|\mathbf{x}}(v, w|x) F_{\mathbf{x}}(x), \end{aligned} \tag{8}$$

where $F_{\mathbf{x}}(x) = \text{Prob}(\mathbf{x} \le x)$ and $S_{\mathbf{v},\mathbf{w}|\mathbf{x}}(v, w|x) = \text{Prob}(\mathbf{v} \ge v, \mathbf{w} \ge w|\mathbf{x} \le x)$.

Moreover, let $\mathbf{z} = (z_1, \dots, z_r) \in \Re^r$ denote the environmental (exogenous) factor which influences the production process (in our case is the GDP per capita-GDPPC).[4] Then Eq. (7) becomes:

$$H_{\mathbf{v},\mathbf{w},\mathbf{x}|\mathbf{z}}(x, v, w|z) = \text{Prob}(\mathbf{x} \le x, \mathbf{v} \ge v, \mathbf{w} \ge w|\mathbf{z} = z), \tag{9}$$

which completely characterizes the environmental production process under the effect of an external variable. The expression in (9) can be decomposed as:

$$\begin{aligned} &H_{\mathbf{v},\mathbf{w},\mathbf{x}|\mathbf{z}}(x, v, w|z) \\ &\quad = \text{Prob}(\mathbf{v} \ge v, \mathbf{w} \ge w|\mathbf{x} \le x, \mathbf{z} = z)\text{Prob}(\mathbf{x} \le x|z) \\ &\quad = S_{\mathbf{v},\mathbf{w}|\mathbf{x},\mathbf{z}}(v, w|x, z) F_{\mathbf{x}|\mathbf{z}}(x|z). \end{aligned} \tag{10}$$

The estimator of the conditional survival function introduced above can be obtained from[5]:

$$\hat{S}_{\mathbf{v},\mathbf{w}|\mathbf{x},\mathbf{z}}(v, w|x, z) = \frac{\sum_{i=1}^{n} I(\mathbf{v}_i \ge v, \mathbf{w}_i \ge w, \mathbf{x}_i \le x) K_h(\mathbf{z}_i, z)}{\sum_{i=1}^{n} I(\mathbf{x}_i \le x) K_h(\mathbf{z}_i, z)}. \tag{11}$$

Simar and Vanhems (2012) developed the probabilistic characterization of directional distance function which according to (5) will take the following form:

$$\begin{aligned} &D(\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w) \\ &\quad = \sup\{\phi > 0 | H_{\mathbf{v},\mathbf{w},\mathbf{x}} \left(\mathbf{v}^0 + \phi\mathbf{g}^v, \mathbf{w}^0 - \phi\mathbf{g}^w, \mathbf{x}^0\right) > 0\}. \end{aligned} \tag{12}$$

---

[1] For dual formulations on weak disposability of undesirable outputs see Kuosmanen and Matin (2011).

[2] Kuosmanen (2005) was the first to coin the term "θ" as the "abatement factor".

[3] For the theoretical background and the asymptotic properties of nonparametric conditional efficiency measures see Jeong et al. (2010).

[4] The earlier studies by Selden and Song (1994) and Grossman and Krueger (1995) suggest that there is an inverted U-type relationship (Environmental Kuznets Curve-EKC) between economic development and environmental damages.

[5] Where $K(\cdot)$ is a univariate kernel with compact support (Epanechnikov in our case) and h is the appropriate bandwidth calculated following the approach by Bădin et al. (2010).

Therefore we can define the conditional directional distance function of ($\mathbf{v}$, $\mathbf{w}$, $\mathbf{x}$) conditioned on $\mathbf{z} = z$ as:

$$D(\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w|\mathbf{z}) = \sup\{\phi > 0 | H_{\mathbf{v},\mathbf{w}|\mathbf{z},\mathbf{x}}(\mathbf{v}^0 + \phi\mathbf{g}^v, \mathbf{w}^0 - \phi\mathbf{g}^w, \mathbf{x}^0|\mathbf{z} = z) > 0\}. \quad (13)$$

Finally, the proposed DEA-based estimator measuring regions' environmental efficiency[6] based on Kuosmanen (2005) technology under the assumption of variable returns to scale (Banker et al., 1984) can be calculated as:

$$\hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w|\mathbf{z}) = \max\phi$$

$$\begin{aligned} \text{Subject to} \quad & \sum_{\substack{k=1,\ldots,K| \\ |\mathbf{z}_k - z| \le h}} \lambda^k v_m^k \ge v_m^0 + \phi g_m^v, \quad \forall m \\ & \sum_{\substack{k=1,\ldots,K| \\ |\mathbf{z}_k - z| \le h}} \lambda^k w_j^k = w_j^0 - \phi g_j^w, \quad \forall j \\ & \sum_{\substack{k=1,\ldots,K| \\ |\mathbf{z}_k - z| \le h}} (\lambda^k + \mu^k) x_n^k \le (\lambda^k + \mu^k) x_n^0, \quad \forall n \qquad (14) \\ & \sum_{\substack{k=1,\ldots,K| \\ |\mathbf{z}_k - z| \le h}} (\lambda^k + \mu^k) = 1 \\ & \lambda^k, \quad \mu^k \ge 0, \quad \forall k. \end{aligned}$$

In linear problem (14) we model the direct influence of the exogenous variable $\mathbf{z}$ (in our case GDP per capita),[7] which in turn it shapes the environmental production frontier. Therefore, the environmental efficiency estimates obtained are determined by the inputs (capital stock and total labor force), the good output (regional GDP), the bad output (regional carbon dioxide emission levels) and the exogenous variable (regional GDP per capita) accordingly.[8] As a result the conditional directional distance function is obtained only by points taking their $\mathbf{z}$ value in the neighborhood of z (Daraio and Simar, 2005).

In order to identify the effect of per capita regional economic growth ($\mathbf{z}$) on regions environmental efficiency (REE) levels without specifying in prior any functional relationship, our paper applies a nonparametric regression in the principles of Daraio and Simar (2005). When $\mathbf{z}$ is univariate (as in our case), a scatter plot of the ratio $\hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w|\mathbf{z}) / \hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w)$ against $\mathbf{z}$ and its smooth nonparametric regression line would be able to describe the effect of $\mathbf{z}$ on regions' environmental efficiency levels. Finally, the nonparametric regression smoothing can be presented as:

$$Q = g(\mathbf{z}_k) + \varepsilon_k, \quad k = 1, \ldots, K, \qquad (15)$$

where $Q = \frac{\hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w|\mathbf{z})}{\hat{D} = (\mathbf{v}^0, \mathbf{w}^0, \mathbf{x}^0; \mathbf{g}^v; \mathbf{g}^w)}$, and ε_k is the error term with $E(\varepsilon_k|\mathbf{z}_k) = 0$, and g is the mean regression function, since $E(Q|\mathbf{z}_k) = g(\mathbf{z}_k)$.[9]

Since we use output oriented conditional and unconditional directional distance functions an increasing regression line will indicate a favorable exogenous factor, whereas a decreasing regression line will indicate an unfavorable factor.

Table 1
Results of the conditional and unconditional environmental efficiency scores.

States	REE	REE|z
Alabama	0.9908	0.2569
Alaska	0.9965	0.1261
Arizona	0.9945	0.2636
Arkansas	0.9869	0.1381
California	1.0000	1.0000
Colorado	0.9874	0.2315
Connecticut	0.9765	0.1231
Delaware	0.9876	0.0466
District of columbia	1.0000	0.0275
Florida	1.0000	0.6263
Georgia	0.9886	0.3749
Hawaii	0.9862	0.0979
Idaho	0.9909	0.0722
Illinois	0.9897	0.5713
Indiana	0.9913	0.3707
Iowa	0.9816	0.1654
Kansas	0.9860	0.1628
Kentucky	1.0000	0.2769
Louisiana	1.0000	0.2907
Maine	0.9768	0.1022
Maryland	0.9845	0.2192
Massachusetts	0.9795	0.2517
Michigan	0.9833	0.4153
Minnesota	0.9817	0.2454
Mississippi	0.9853	0.1212
Missouri	0.9834	0.3021
Montana	0.9940	0.2123
Nebraska	0.9824	0.1200
Nevada	0.9989	0.1118
New Hampshire	0.9769	0.0990
New Jersey	0.9865	0.3533
New Mexico	0.9873	0.1248
New York	1.0000	0.6557
North Carolina	0.9935	0.3505
North Dakota	1.0000	0.5572
Ohio	0.9877	0.5023
Oklahoma	0.9898	0.1959
Oregon	0.9750	0.1339
Pennsylvania	0.9913	0.5750
Rhode Island	0.9678	0.0966
South Carolina	0.9844	0.1930
South Dakota	0.9803	0.1764
Tennessee	0.9837	0.2684
Texas	1.0000	1.0000
Utah	0.9933	0.1387
Vermont	1.0000	0.2604
Virginia	0.9921	0.2891
Washington	0.9883	0.2173
West Virginia	1.0000	0.1896
Wisconsin	0.9825	0.2582
Wyoming	1.0000	1.0000
Descriptives	**REE**	**REE|z**
Mean	0.9891	0.2933
Std	0.0081	0.2339
Median	0.9883	0.2315
Max	1.0000	1.0000
Min	0.9678	0.0275

[6] Here we are using efficiency estimates rather that inefficiencies by adopting the transformation by Chung et al. (1997) and Chambers et al. (1998). According to Podinovski and Kuosmanen (2011) the conventional radial Farrell input and output efficiency measures can be obtained as special cases of the directional distance functions.

[7] According to the EKC hypothesis environmental degradation increases with low levels of per capita income and then it decreases when a certain threshold level is reached. Taskin and Zaim (2000) and Zaim and Taskin (2000) provide evidence of an inverted U-type relationship between environmental efficiency and per capita income. However, Managi (2006, p. 618) provides a detail literature review of EKC studies suggesting that there is no single relationship between environmental pollution and per capita income that fits all types of pollutants, regions, and time periods.

[8] All the variables used in our empirical application are referring to 2005 and they have extracted from OECD regional database. Moreover, since there is not any data available for US states' capital stock we have used the perpetual inventory method. Therefore states' capital stock can be calculated as: $K_t = I_t + (1-\delta)K_{t-1}$ where K_t is the state's gross capital stock in current year; K_{t-1} is the state's gross capital stock in the previous year; I_t is the state's gross fixed capital formation and δ represents the depreciation rate of capital stock. In our study we have set δ equal to 6%.

[9] In our case we use the Nadaraya (1964) and Watson (1964) nonparametric regression estimator and the least square cross-validation data driven method (Hall et al., 2004) for the bandwidth selection.

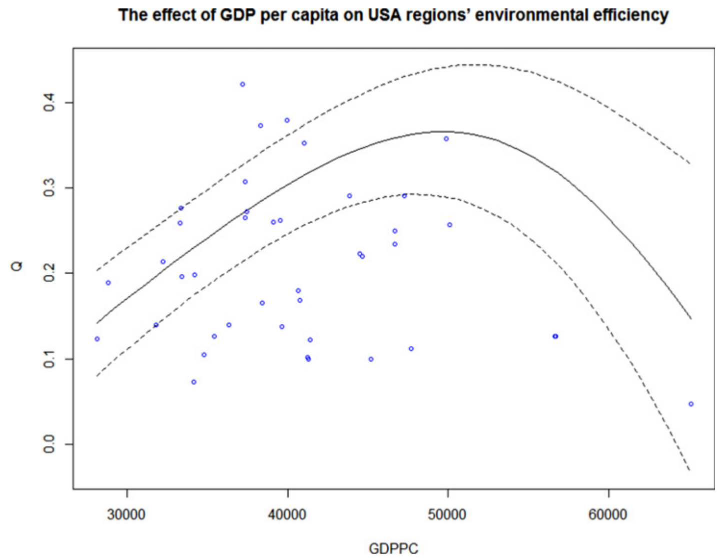

Fig. 1. Influence of economic growth on US regions' environmental efficiency.

3. Empirical findings

Table 1 presents the results of the unconditional (REE) and conditional (REE|z) regional environmental efficiency estimates as derived from our proposed estimator. The unconditional environmental efficiency results reveal that 11 out of 51 states are reported to be environmentally efficient in terms of carbon dioxide emissions. The descriptive statistics show that all the US regions have similar environmental efficiency levels indicated by the low values of standard deviation (0.0081). Also high environmental efficiency values are reported among the US regions with a mean value of 0.9891.

However when we account for the effect of regions' GDP per capita levels, their environmental efficiency levels are much lower. Under the conditional environmental efficiency estimates only three states are environmental efficient. The mean value of the estimated conditional environmental efficiency is 0.2933 with a high standard deviation (0.2339).

In several cases, the effect of regions' economic growth has decreased their environmental efficiency levels. Under the case of unconditional environmental measures the states of District of Columbia, Florida, Kentucky, Louisiana, New York and North Dakota have been reported to be environmental efficient. However, under the effect of their GDP per capita level, their environmental efficiency levels have been decreased.

Finally, Fig. 1 presents graphically the global effect of states' GDP per capita (GDPPC) on their environmental efficiency levels.[10] As has been analyzed previously an increasing nonparametric line indicates a positive effect on regions' environmental efficiency levels whereas a decreasing line indicates a negative effect. The results indicate that the relation of states' economic growth–environmental efficiency levels has an inverted 'U' shape form. This is indicated by an increasing nonparametric regression line (up to a certain GDP per capita level of approximately 49,000$) which is followed by a deterioration of US regions' environmental efficiency levels.[11]

4. Conclusions

In this paper, we propose an extension of Kuosmanen's (2005) DEA-type estimator incorporating exogenous factors for measuring environmental efficiency levels by using conditional directional distance functions (Simar and Vanhems, 2012). We apply our estimator investigating the effect of regional GDP per capita on US regions' environmental efficiency levels. The empirical results reveal that under the effect of regional GDP per capita the regions' environmental efficiency levels are decreasing. Finally, the nonparametric regression analysis reveals that the examined relationship has an inverted "U" shape form.

Acknowledgments

We would like to thank the editor (Professor Badi H. Baltagi) and an anonymous reviewer for the comments raised to an earlier version of our paper. Any remaining errors are solely the authors' responsibility.

References

Bădin, L., Daraio, C., Simar, L., 2010. Optimal bandwidth selection for conditional efficiency measures: a data-driven approach. European Journal of Operational Research 201, 633–640.

Banker, R.D., Charnes, A., Cooper, W.W., 1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis. Management Science 30, 1078–1092.

Cazals, C., Florens, J.P., Simar, L., 2002. Nonparametric frontier estimation: a robust approach. Journal of Econometrics 106, 1–25.

Chambers, R.G., Chung, Y., Färe, R., 1998. Profit, directional distance functions, and Nerlovian efficiency. Journal of Optimization Theory and Applications 98, 351–364.

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

Daraio, C., Simar, L., 2005. Introducing environmental variables in nonparametric frontier models: a probabilistic approach. Journal of Productivity Analysis 24, 93–121.

10 From our analysis we excluded the state of District of Columbia since it has a significant higher GDP per capita level (142,319$) compared to the sample mean value (41,248$) and acts as a potential outlier. In addition the dotted lines in Fig. 1 indicate the bootstrapped pointwise error bounds (Racine, 2008).

11 However it must be mentioned that the U-shape relationship between states' environmental efficiency and their GDP per capita levels is characterized mainly by the GDP per capita levels of three states (Delaware: 65,154$; Alaska: 56,697$; Connecticut: 56,670$). If we exclude also these three states from the analysis and we treat them as outliers (as in the case of District of Columbia) then we will have a monotonic increasing relationship between states' environmental efficiency and their GDP per capita levels.

Grossman, G.M., Krueger, A.B., 1995. Economic growth and the environment. Quarterly Journal of Economics 110, 353–377.
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.
Jeong, S.O., Park, B.U., Simar, L., 2010. Nonparametric conditional efficiency measures: asymptotic properties. Annals of Operations Research 173, 105–122.
Kuosmanen, T., 2005. Weak disposability in nonparametric productivity analysis with undesirable outputs. American Journal of Agricultural Economics 87, 1077–1082.
Kuosmanen, T., Matin, R.K., 2011. Duality of weakly disposable technology. Omega 39, 504–512.
Kuosmanen, T., Podinovski, V., 2009. Weak disposability in nonparametric production analysis: reply to Färe and Grosskopf. American Journal of Agricultural Economics 91, 539–545.
Managi, S., 2006. Are there increasing returns to pollution abatement? empirical analytics of the Environmental Kuznets Curve in pesticides. Ecological Economics 58, 617–636.
Nadaraya, E.A., 1964. On estimating regression. Theory of Probability and its Applications 9, 141–142.
Podinovski, V.V., Kuosmanen, T., 2011. Modelling weak disposability in data envelopment analysis under relaxed convexity assumptions. European Journal of Operational Research 3, 577–585.
Racine, J.S., 2008. Nonparametric econometrics: a primer. Foundations and Trends in Econometrics 3, 1–88.
Selden, T., Song, D., 1994. Environmental quality and development: is there a Kuznets curve for air pollution emissions?. Journal of Environmental Economics and Management 27, 147–162.
Simar, L., Vanhems, A., 2012. Probabilistic characterization of directional distances and their robust versions. Journal of Econometrics 166, 342–354.
Taskin, F., Zaim, O., 2000. Searching for a Kuznets curve in environmental efficiency using kernel estimation. Economics Letters 68, 217–223.
Watson, G.S., 1964. Smooth regression analysis. Sankhyā 26, 359–372.
Zaim, O., Taskin, F., 2000. A Kuznets curve in environmental efficiency: an application on OECD countries. Environmental and Resource Economics 17, 21–36.