The good, the bad and the ugly? Balancing environmental and economic impacts towards efficiency

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Abstract

This paper estimates the efficiency of the power generation sector in the USA by using Window Data Envelopment Analysis (W-DEA). We integrate radial and non-radial efficiency measurements in DEA using the hybrid measure while we extend the proposed model by considering inputs and good and bad outputs as separable and non separable. Then in the second stage analysis we perform various econometric techniques (parametric and non-parametric) in order to model the relationship between the calculated environmental efficiencies and economic growth in attaining sustainability. Our empirical findings indicate an N-shape relationship between environmental efficiency and regional economic growth in the case of global and total pollutants but an inverted N-shape in the case of assessing local pollutants and using the appropriate dynamic specification. This implies that attention is required when considering local and global pollutants and the extracted environmental efficiencies.

Keywords: Energy; Efficiency; Sustainability; Window DEA; Electricity; EKC hypothesis; USA.

JEL Codes: C23; C67; O13; Q01; Q48; Q53; Q56.

1. Introduction

There is a general consensus among policy makers and government officials that electricity industry constitutes the largest emitting sector in the USA with a total carbon dioxide (CO_2) emissions amounting up to 2.2 billion metric tones in 2012 (IEA, 2014). It is noteworthy that at the end of 2012, power generation sector accounted for 31% of total anthropogenic Greenhouse Gas Emissions (GHG).

Although there is a striking need for reducing emissions generated by the electricity sector to meet environmental goals, most of the existing studies focus mainly on the examination of the link between environmental efficiency and economic growth known as Environmental Kuznets Curve (EKC) hypothesis, ignoring the role of the electricity sector (Halkos and Tzeremes, 2013a; Managi, 2006; Daraio and Simar, 2005; Millimet et al., 2003; Zaim and Taskin, 2000; Taskin and Zaim, 2000).[1] On the other hand, many empirical studies assess the efficiency of the electricity industry neglecting its role to the environmental degradation (see among others Goto and Tsutsui, 1998; Vanisky, 2006; Kounetas, 2015). Our study aims to cover these caveats by linking the level of electricity efficiency with environmental concern.

The majority of the existing studies devoted on testing an EKC hypothesis estimate reduced-form equations that enter the model either in a parametric (piecewise linear, quadratic, cubic models) or in a nonparametric form (i.e. semiparametric, partially linear models, etc).[2] More specifically, Millimet et al. (2003) explore the importance of modeling strategies when estimating the emissions-income relationship. Similarly to our study, they use USA state-level panel data on two air pollutants (NO_x

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[1] EKC hypothesis implies a non linear relationship of an inverted ‘U’ type between environmental degradation and economic growth. Reasons justifying the EKC may be found among others in Halkos (2012, 2013).

[2] For a survey of the EKCs on an empirical and theoretical perspective see the relevant studies of Dinda (2004) and Kijima et al. (2010) respectively.

and SO_2) in order to estimate several EKCs by comparing parametric and semiparametric techniques. They argue in favor of the more flexible semiparametric approach confirming the existence of an inverted U-shape between emissions and regional economic growth.

Halkos and Tzeremes (2013a) investigate the link between regional environmental efficiency and economic growth by applying a nonparametric model employed in Daraio and Simar (2005). They argue that there is an inverted ‘*U*’ shape relationship between regional environmental efficiency and USA state per capita income. The opposite finding is evident in Halkos and Tzeremes (2013b) in which a conditional directional distance function DEA approach was used in order to incorporate the effect of regional economic growth on regions’ environmental efficiency levels in the UK. The results reveal a ‘*U*’ shape form between economic growth and environmental inefficiency.

Other researchers (see for example Bruyn and Opschoor, 1997; Sengupta, 1997) claim that some indicators such as CO_2 emissions exhibit an N shape, meaning that the environmental degradation starts increasing again after a decrease to a certain level. Lastly, Madisson (2006) extents the notion of the EKC nexus by estimating a spatial panel data model of 135 OECD countries in order to capture the impact of economic growth on several air pollutants (SO_2, NO_X, CO and VOC emissions). The study concludes that national SO_2 and NOx emissions are strongly influenced by the emissions per capita of neighbouring countries. Moreover, it is argued that national NO_X emissions per capita are decreased by proximity to high per capita income countries which is inconsistent with countries achieving higher environmental quality at the expense of their neighboring countries.

On the other hand, relatively few empirical studies adopt a simultaneous equations system in order to address the impact of economic growth on environmental degradation. In the seminal paper of Dean's (2002), a panel simultaneous equations system is built around a Heckscher-Ohlin model capturing thus certain effects of trade liberalization on the environmental quality (water pollution). The sample included 28 Chinese provinces over the period 1987-1995 and the empirical findings suggest that there is a direct negative trade effect on environmental damage, which is fully reversed when the income growth is taken into account. In a more recent paper, Jayanthakumaran and Liu (2012) try to assess the relationship in China between trade, growth and emissions using provincial panel data for water and air pollution over the period 1990–2007. They use a variety of econometric techniques ranging from a quadratic log function specification to a simultaneous equations system similar to Dean's approach. The major contribution of this paper was to shed light on the empirical evidence for both the EKC and the trade related emissions hypothesis. Their findings are rather mixed providing little support in favor of the EKC hypothesis.

The contribution of our paper is three-fold. First, it goes beyond the existing literature in that it uses a micro level dataset originated from nearly 789 power plants on 50 USA regions (states). Second, it utilizes a Window Data Envelopment Analysis (hereafter W-DEA) approach with certain innovations such as the radial and non-radial efficiency measurements and the treatment of inputs and outputs (good and bad) as separable and non separable. Third, and most importantly, the paper concurs that there is a stable N-shaped relationship between environmental efficiency (in each of the three pollution models) and regional economic growth. Taken together, this set of findings is important in that it provides some useful policy implications towards the abatement of air pollution in order to achieve sustainability.

The rest of the paper is organized as follows. Section 2 introduces the data and describes the methodology, while Section 3 discusses the empirical findings. Finally, Section 4 concludes the paper.

2. Data and Methodology

In order to estimate electricity efficiency, we use the utilization of net capacity (UNC) as a proxy for good output, while three '*bad*' outputs accounting for CO_2, SO_2 and NOx emissions are incorporated in our analysis.[3] The inputs in the production process are total energy losses, as a proxy for capital and total operating cost, as a proxy for labor. The latter combines expenses of labor, materials, depreciation, and several other cost components, while the former captures all electricity losses that occur between the points of generation (power plants) and the transportation and distribution of electricity through high and low voltage power grids (infrastructure) to final consumers (see for example Vaninsky, 2006).

In contrast, many studies (Fare et al., 1989, 1996, 2004; Fare and Grosskopf, 2003, 2004; Chung et al., 1997; Tyteca, 1996, 1997; Taskin and Zaim, 2001; Zofio and Prieto, 2001; Zaim, 2004; Managi, 2006; Yoruk and Zaim, 2006; Picazo-Tadeo and Garcia-Reche, 2007; Picazo et al., 2012; Halkos and Tzeremes, 2009a; Halkos and Tzeremes, 2013b; Zhang et al., 2011) use the capital stock and since they do not have available data on a regional basis, they often use the perpetual inventory method taking into account a uniform depreciation rate $\delta = 6\%$.[4] However, since capital stock includes several capital assets (i.e. transportation, machinery, buildings, etc) a uniform depreciation rate seems unrealistic. Our proposed method deals with this issue.

Moreover, we assume that the two inputs affect the good output in a separable way since either energy losses or operating cost of a power plant are linked with its production process (net generation). In contrast, the production of the good output

[3] Utilization of net capacity is given by $UNC = \dfrac{Net\ Generation}{Summer + Winter\ Peak\ Demand}$.

[4] This method calculates the capital stock 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 is the depreciation rate.

generates air pollutants distorting the environmental conditions in a non-separable way.

2.1 Descriptive statistics

All the above variables are obtained by the Energy Information Administration (EIA), while per capita real GDP (in 2009 prices) by state is drawn from the Regional Economic Accounts of the Bureau of Economic Analysis.[5] Data are collected for a sample of 650 observations, relative to primarily annual information from EIA energy statements of an unbalanced micro panel of nearly 789 electric utilities operating in 50 US states spanning the period 2000 to 2012. The choice of the time period is dictated strictly by data availability.

Summary statistics for the variables are provided in the following table. From the relevant table, it is evident that the sample data are well behaved showing limited variability in relation to the mean except for the net capacity (good output) where the coefficient of variation exceeds one. On the other hand, the variables are not normally distributed since the relative values of the skewness and kurtosis measures are not equal to zero and three, respectively. This is also confirmed by the Jarque-Bera statistic in which the null hypothesis is rejected in all of the cases indicating that the variables do not follow the normal (Gausian) distribution.

[5] Similarly to Halkos and Tzeremes (2013a) we excluded the state of District Columbia (DC) that acted as a potential outlier.

Table 1: Descriptive statistics

	Bad Outputs			Good output	Inputs		Income variable
Statistical measures	CO_2	SO_2	NO_X	*Net Capacity*	*Energy Losses*	*Total Cost*	*Real GDP/capita*
Observations	650	650	650	650	650	650	650
Mean	48,322,510.000	171,634.000	75,344.130	1,638.537	4,750,821.000	82,019.660	45,498.860
Median	38,227,289.000	83,359.500	60,693.500	1,561.284	3,184,037.000	42,547.000	44,055.000
Maximum	267,000,000.000	1,152,407.000	510,931.000	137,366.7	27,299,280.000	1,321,369.000	70,918.000
Minimum	6,583.000	28.000	409.000	-0.007	1151.000	94.000	28,957.000
Standard deviation	45,569,866.000	219,004.300	70,755.920	5,403.526	5,139,173.000	137,111.200	8,373.095
Skewness	2.128	2.008	1.832	24.43581	1.871	5.284	0.726
Kurtosis	9.744	7.167	7.503	614.324	6.500	39.750	3.232
Coefficient of variation	0.943	1.276	0.939	3.298	1.082	1.672	0.184
Jarque-Bera	1,722.461	907.063	912.638	10,186,188	710.967	39,602.000	58.612
P-value (Jarque-Bera)	0.000	0.000	0.000	0.000	0.000	0.000	0.000

2.2 The radial separable Data Envelopment Analysis

Data Envelopment Analysis (hereafter DEA) method may be used for the evaluation of a decision making unit (DMU) efficiency relative to other DMUs. DEA has been used in calculating relative efficiencies in various applications. The main problem in applying DEA in the presence of undesirable outputs is that efficiency is attained by minimizing inputs and maximizing outputs. But in the case of bad outputs we may wish to maintain same inputs with more good output and less bad output. Thus bad outputs demand a special treatment in model formulations.

Koopmans (1951) mentioned that some undesirable outputs like pollutant emissions and wastes disposal affect negatively the environment and should be reduced. In these lines Fare et al. (1989) differentiated outputs as desirable (good) and undesirable (bad) outputs and suggested a non-linear programming model in calculating DMUs efficiencies in the presence of both desirable and undesirable outputs. Since then several scholars have proposed efficiency measurements in the case of undesirable outputs.

One way to tackle this problem is to shift undesirable outputs into inputs and apply DEA. Seiford and Zhu (2002) provided radial measures assuming efficiency may be improved by increasing good and decrease bad outputs simultaneously. For doing so a multiplication of bad outputs by -1 is proposed and with the use of an adequate translation vector to transform all negative bad outputs to be positive. These two transformations of changing position and translation provide the same efficient frontiers (Scheel 2001) with the Seiford and Zhu method to be valid in the case of variable returns to scale (VRS) and the two methods to provide different inefficiency scores.

Another way is to empower bad output and to consider it as a good output. Fare et al. (1989) treated good and bad outputs asymmetrically measuring environmental technology in a production function setup with the use of distance functions non-parametrically. At the same time by imposing strong and weak disposability they calculated environmental performance indicators. As Cooper et al. (2007) point out a drawback of radial models is that they disregard slacks when dealing with bad outputs slacks are not accounted in the efficiency measurement.

The radial method is applied in Charnes, Cooper and Rhodes (CCR) and Banker, Charnes and Cooper (BCC) models with ignorance of non-radial input and output slacks.[6] Similarly the non-radial method of slack based method copes with slacks but it ignores the radial inputs and outputs. To tackle this problem we integrate radial and non-radial efficiency measurements in DEA using the hybrid measure while we extend the proposed model by considering inputs and good and bad outputs as separable and non separable.[7] If n, γ and s correspond to the number of DMUs, inputs and outputs and $X \in R^{\gamma x n}$ and $Y \in R^{sxn}$ the observed input and output data

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[6] See Charnes et al. (1978) and Banker et al. (1984) respectively.
[7] Hybrid was proposed in Tone (2004).

matrices then the decomposition of radial and non-radial parts of inputs and outputs $X^R \in R^{\gamma_1 xn}$, $X^{NR} \in R^{\gamma_2 xn}$ with $\gamma=\gamma_1+\gamma_2$ and $Y^R \in R^{s_1 xn}$, $Y^{NR} \in R^{s_2 xn}$ with $s=s_1+s_2$ may be expressed as

$$X = \begin{pmatrix} X^R \\ X^{NR} \end{pmatrix} \qquad\qquad Y = \begin{pmatrix} Y^R \\ Y^{NR} \end{pmatrix} \tag{1}$$

Assuming a positive data set with X,Y>0 the production possibility set P and for a constant returns to scale formulation is expressed as:

$$P = \{x, y) \,|\, x \geq X\lambda, \;\; y \leq Y\lambda, \;\; \lambda \geq 0\} \tag{2}$$

For a specific $DMU_0(x_0,y_0)$=$DMU_0\left(x_0, y_0\right) = (x_o^R, x_o^{NR}, y_o^R, y_o^{NR}) \in P$ we have

$$\begin{aligned} \alpha x_o^R &= X^R\lambda + s^{R-} \\ x_o^{NR} &= X^{NR}\lambda + s^{NR-} \\ \zeta y_o^R &= Y^R\lambda - s^{R+} \\ y_o^{NR} &= Y^{NR}\lambda - s^{NR+} \end{aligned} \tag{3}$$

With $\alpha \leq 1$, $\zeta \geq 1$, and $\lambda, s^{R-}, s^{NR-}, s^{R+}, s^{NR+} \geq 0$. The slacks are represented by the vectors $s^{R-} \in R^{\gamma_1}$ and $s^{NR-} \in R^{\gamma_2}$ corresponding to the excesses for the radial and non-radial inputs and $s^{R+} \in R^{s_1}$ and $s^{NR+} \in R^{s_2}$ for the losses of the radial and non-radial outputs.

Following Cooper et al. (2007) a feasible expression is with $\alpha=1$, $\zeta=1$, $\lambda_0 \geq 1$, $\lambda_j=0$ and with zero slacks. An index ρ is defined as

$$\rho = \frac{1 - \frac{\gamma_1}{\gamma}(1-\alpha) - \frac{1}{\gamma}\sum_{i=1}^{\gamma_2} \frac{s_i^{NR-}}{x_{io}^{NR}}}{1 + \frac{s_1}{s}(\zeta - 1) + \frac{1}{s}\sum_{k=1}^{s_2} \frac{s_k^{NR+}}{y_{k_0}^{NR}}} \tag{4}$$

Then $DMU_0\left(x_0, y_0\right)$ is hybrid efficient if $\alpha = 1$, $\zeta = 1, s^{NR-} = 0$, $s^{NR+} = 0$.

At this time suppose we have n DMUs using γ inputs and producing a good and a bad output. With the vectors of inputs, and of good and bad outputs being $x \in R^{\gamma}$, $y^G \in R^{s_1}$ and $y^B \in R^{s_2}$ respectively and with the matrices $X = [x_1, ..., x_n] \in R^{\gamma x n}$, $Y^G = [y_i^G, ..., y_n^G] \in R^{s_1 x n}$ and $Y^B = [y_i^B, ..., y_n^B] \in R^{s_2 x n}$ then assuming X, Y^G, Y^B >0 the production possibility set is presented as

$$P = \{x, y^G, y^B) \big| x \geq X\lambda,\ y^G \leq Y^G\lambda,\ y^B \geq Y^B\lambda,\quad \lambda \geq 0\} \tag{5}$$

and a $DMU_0(x_0, y_o^G, y_o^B)$ is efficient in the case of bad outputs if there is not any vector $(x, y^G, y^B) \in P$ with at least one strict inequality and $x_o \geq x,\ y_o^G \leq y^G,\ y_o^B \geq y^B$. In this case we have the following expression:

$$\rho^* = \min \frac{1 - \frac{1}{\gamma}\sum_{i=1}^{\gamma}\frac{S_i^-}{x_{io}}}{1 + \frac{1}{s_1 + s_2}\left((\sum_{k=1}^{s_1}\frac{S_k^G}{y_{k_0}^G} + \sum_{k=1}^{s_2}\frac{S_k^B}{y_{k_0}^B} \right)} \tag{6}$$

Subject to

$$\begin{aligned} x_o &= X\lambda + s^- \\ x_o^G &= X^G\lambda - s^G \\ y_o^B &= Y^B\lambda + s^B \end{aligned} \tag{7}$$

$$s^- \geq 0,\ s^G \geq 0,\ s^B \geq 0,\ \lambda \geq 0.$$

Now, the vectors $s^- \in R^{\gamma}$ represent the excesses in inputs, $s^B \in R^{s_2}$ in bad outputs and $s^G \in R^{s_1}$ the losses in good outputs (Cooper et al., 2007).

At this moment it is worth considering that environmental undesirable outputs like pollutants emissions are not separable from the associated desirable output and a reduction in undesirable outputs comes together with a reduction in the desirable output. There is an inseparability issue between bad outputs and good outputs but possibly also certain inputs. In this case we separate the set of outputs (Y^G, Y^B) into separable good (Y^{S_G}) and non separable good and bad outputs (Y^{NS_G}, Y^{NS_B}). The same applies also to the inputs (X^S, X^{NS}) with the case of separable inputs being $X^S \in R^{\gamma_1 xn}$ and non separable $X^{NS} \in R^{\gamma_2 xn}$. Although for the case of separable good outputs (Y^{S_G}) we have the same form of production as Y^G in P, in the case of non separable outputs (Y^{NS_G}, Y^{NS_B}) we have:

$$P_{NS} = \{(X^S, X^{NS}, Y^{S_G}, Y^{NS_G}, Y^{NS_B}) \ | x^S \geq X^S\lambda,\ x^{NS} \geq X^{NS}\lambda,\ y^{S_G} \leq Y^{S_G}\lambda,$$
$$y^{NS_G} \leq Y^{NS_G}\lambda,\ y^{NS_B} \geq Y^{NS_B}\lambda,\ \lambda \geq 0\} \tag{8}$$

and a $DMU_0(x_o^S, x_o^{NS}, y_o^{S_G}, y_o^{NS_G}, y_o^{NS_B})$ is non separable efficient if for any μ (0≤μ≤1) $(x_o^S, x_o^{NS}, y_o^{S_G}, \mu y_o^{NS_G}, \mu y_o^{NS_B}) \notin P_{NS}$ and together with at least one strict inequality $x_0^S \geq x^S,\ x_0^{NS} \geq x^{NS}, y_o^{S_G} \leq y^{S_G},\ y_o^{NS_G} = y^{NS_G},\ y_o^{NS_B} = y^{NS_B}$. Similar to Cooper et al. (2007) in this case the corresponding hybrid model can be expressed as:

$$\rho^* = \min \frac{1 - \frac{1}{\gamma}\sum_{i=1}^{\gamma_1} \frac{S_i^{S^-}}{x_{io}} - \frac{\gamma_2}{\gamma}(1-\mu)}{1 + \frac{1}{s}\left((\sum_{k=1}^{s_{11}} \frac{S_r^{S_G}}{y_{k_0}^{S_G}} + (s_{21} + s_{22})(1-\mu) \right)} \tag{9}$$

Subject to

$$X_0^S = X_S\lambda + s^{S^-}$$
$$\mu X_0^{\mathrm{NS}} = X_{\mathrm{NS}}\lambda$$
$$Y_0^{S_G} = Y_{S_G}\ \lambda + s^{S_G} \tag{10}$$
$$\mu Y_0^{\mathrm{NS}_G} \leq Y^{\mathrm{NS}_G}\lambda$$
$$\mu Y_0^{\mathrm{NS}_B} \leq Y^{\mathrm{NS}_B}\lambda$$

$$s^{s-} \geq 0, \quad s^{s_G} \geq 0, \lambda \geq 0, \quad 0 \leq \mu \leq 1$$

2.3 The proposed model for measuring environmental efficiency

DEA window analysis was proposed by Charnes et al. (1985) dealing with panel data and relying on the principle of moving average. In this analysis each DMU is considered as a different DMU and every DMU's performance is compared both with the performance of the other DMUs and with its own performance through time. To perform a DEA window analysis in the case of N DMUs (n=1, 2, … , N) using γ inputs and δ outputs in T time periods (t=1, 2, … , T) this will produce a sample of NxT observations where an observation n in period t (DMU_t^n) has an γ dimensional input vector x_n^t and an s dimensional output vector y_n^t of the form

$$x_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{\gamma t} \end{bmatrix} \qquad y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \tag{11}$$

If the window begins at time v (1≤v≤T) with a width equal to w (1≤w≤T-v) then the inputs and outputs matrices can be presented as

$$x_{vw} = \begin{bmatrix} x_1^v & x_2^v & \cdots & x_N^v \\ x_1^{v+1} & x_2^{v+1} & \cdots & x_N^{v+1} \\ \vdots & \vdots & \cdots & \vdots \\ x_1^{v+w} & x_2^{v+w} & \cdots & x_N^{v+w} \end{bmatrix} \qquad y_{vw} = \begin{bmatrix} y_1^v & y_2^v & \cdots & y_N^v \\ y_1^{v+1} & y_2^{v+1} & \cdots & y_N^{v+1} \\ \vdots & \vdots & \cdots & \vdots \\ y_1^{v+w} & y_2^{v+w} & \cdots & y_N^{v+w} \end{bmatrix} \tag{12}$$

The substitution of inputs and outputs in the appropriate model specifications as in the CCR and BCC models provide us with the DEA window analysis results.

The measurement of DMUs' environmental performance using DEA window analysis relies on the calculation of an indicator of the ratio of the quantity index of good output to a quantity of an index of a bad output (among others, Färe et al., 1999, 2000; Zaim et al., 2001; Zaim, 2004). The higher this indicator (ratio of good to bad output) the higher is the DMU's environmental performance.

For the estimation of efficiency changes through time DEA window analysis is applied relying on the idea of a moving average of appropriate width. In this way DMUs are treated as different in each time period. That is, in our case the DMUs are the 50 USA states (N = 50) over a time period of 13 years period (t = 13) and with the imposition of a 3-year (w = 3) window. This implies that each DMU is allocated in the window and it is treated as a different DMU for each of the three years of each window. This leads to a number of windows (nw) equal to 11 (t-w+1) and a number of 1650 different DMUs (N*w*nw=50*3*11). The process starts from window 1 (including years 2000, 2001 and 2002) and ends to the last (11^{th}) window (containing years 2010, 2011 and 2012) and having analyzed in total 1650 different DMUs.

2.4 Econometric framework

In order to capture the effect of per capita economic growth on environmental efficiency levels we have used three parametric and one nonparametric approach. First, similarly to many empirical studies (see for example Millimet et al., 2003; Jayanthakumaran and Liu, 2012), we estimate a two-way OLS fixed-effects panel data model (basic model) using a cubic specification of the following form:

$$EFF_{it} = a_i + \beta_t + b_0 + b_1 GDP_{it} + b_2 GDP_{it}^{\ 2} + b_3 GDP_{it}^{\ 3} + \varepsilon_{it} \tag{13}$$

i = 1,2,…50 and t = 1,2,…13

where EFF_{it} is a vector that includes CO_2 efficiency scores, SO_2 and NO_X efficiency scores and finally CO_2, SO_2 and NO_X efficiency scores for state i at time t; α_i and β_i are state and time fixed effects used in order to capture common factors across the cross-section element; GDP_{it} is real GDP (in constant 2009 prices) per capita for state i at time t; and ε_{it} are zero mean i.i.d. innovations.

However, there is a potential endogeneity issue regarding the use of the polynomial GDP per capita. Because of this, an OLS estimator would tend to underestimate the effect of these control variables on electricity efficiency scores (i.e coefficient biased towards zero). In order to overcome possible endogeneity issues, we re-estimate our basic model by applying two dynamic GMM estimators developed by Arellano and Bond (1991) and Blundell and Bond (1998) respectively. The former estimator is also known as a two-step difference GMM (DIF-GMM) where the lagged levels of the regressors are instruments for the equations in first differences. The latter (System GMM) combines the regression expressed in first differences with the original equation expressed in levels and allows us to include some additional instrument variables (SYS-GMM). The main advantage of having a time lag in the dependent variable is to capture short run and long run effects that cannot be identified by a static model (Halkos, 2003; Polemis, 2016). Endogeneity can be a problem because, if unobserved variables jointly affect both the dependent and control variables, then the coefficient estimates for the independent variables may be biased (Hausman and Ros, 2013). The dynamic GMM set of estimators take into account the unobserved time-invariant bilateral specific effects, while it can deal with the potential endogeneity arising from the inclusion of several control variables.

It is worth mentioning that nearly all of the existing empirical studies assume specific functional forms for their regression relationships. In other words they adopt parametric regression models that often lead to misspecification of their functional form unless it is correctly specified by the economic theory (Tran and Tsionas, 2010). In order to deal with this issue, we rely on panel data nonparametric methodology where little prior restriction is imposed on the model's structure. In this way, we do not have to assume a priory any functional relationship between the electricity efficiency and the level of regional per capita growth. The nonparametric local polynomial smoothing model (LPOLSM) can be written as:

$$EFF_{it} = a_i + \beta_t + g(gdp_{it}) + u_{it} \tag{14}$$

i = 1,2,…50 and t = 1,2,…13

where g(.) is an unknown function, u_{it} is a mean zero residual assumed to be uncorrelated with g(.), α_i are state fixed effects, and finally β_i are time effects. As it is stated, one of the main advantage of the LPOLSM is that in contrast to parametric regression, no linear or nonlinear functional model is postulated for g. The local polynomial estimator of g at a point x_0 is based on a polynomial approximation of g(GDP) near x_0 by minimizing the following formula:[8]

$$\sum_{i=1}^{n}\left(EFF_i - \sum_{j=0}^{p}\beta_j (GDP_i - x_0)^j\right)^2 K\left(\frac{GDP_i - x_0}{h}\right) \tag{15}$$

Subject to β = $(\beta_0,...,\beta_p)'$.

Where *K(.)* is a kernel (nonnegative symmetric weight) function and h = h_n is the bandwidth smoothing parameter for sample size n chosen by cross validation (see for example Brockmann et al., 1993; Fan and Gijbels, 1995 for details). In this case, we could estimate $g(x_o)$ using a local polynomial of the following form:

$$\sum_{j=0}^{p}\hat{\beta}_j (x - x_0)^j \text{ at } x = x_0 \tag{16}$$

Therefore the local polynomial estimator is given by the following equation:

$$\hat{g}(x_0) = \hat{\beta}_0 \tag{17}$$

[8] For presentational simplicity for the observations we only use subscript *i* and omit *t*.

3. Results and discussion

Table 2 presents the results of the regional environmental efficiency estimates as derived from our hybrid model broken down by three pollution models.[9] The efficiency results reveal that in all of the specifications, 4 out of 50 states (Alaska, Hawaii, Utah and Wyoming) are reported to be environmentally efficient in terms of the anthropogenic emissions since their scores are close to unity. On the other hand, 5 out of 50 states report the lowest efficiency values ranging from 0.002 to 0.394. These are Rhode Island, Delaware, New Jersey, Illinois and Ohio.

In terms of the static analysis, the descriptive statistics reveal low disparities of regional environmental efficiencies among US states since the standard deviation and the coefficient of variation (CV) appear to be relatively low ranging from 0.164 to 0.198 and 0.317 to 0.907 respectively. Moreover, on average terms USA states have an environmental efficiency level ranging from 0.218 to 0.516. This means that US regions on average terms are able to reduce their total CO_2, SO_2 and NO_x levels generated by the electricity sector (see Model 1) by 78.2% to reach the efficiency frontier, while also increase their regional economic growth (proxied by per capita GDP) by the same proportion.[10]

In terms of the time series analysis and for Model 1 (see Table A1 in the Appendix), the average annual efficiency scores of electricity sector in each state relative to the state's frontier reveal stability or a slight general improvement for the cases of Alaska, Hawaii, Utah, New Mexico, North Dakota and Wyoming and a slight decline in overall efficiency levels for the cases of California, Delaware, Florida, Georgia, and Texas. The states with the highest mean efficiency scores are Alaska and

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[9] To preserve space, we only report the efficiency scores for the latest available year (2012). The detailed results over the whole examination period are reported in the Appendix (see Tables A1, A2 and A3).

[10] Since the mean environmental efficiency score for the extended (full) model equals to 0.218 or 21.8%, the rest amount 0.782 (78.2%) denotes the inefficiency score.

Hawaii with 93.2% and 80.5% respectively, while the states with the lowest values are Maryland (5%) and Ohio (5.1%). It is worth mentioning that similar results are obtained in the other two specifications (see Tables A2 and A3).

Lastly, our findings are on average terms in alignment with the study of Halkos and Tzeremes (2013a) who estimate the efficiency scores for the US states for the year 2005. However, the DEA efficiency scores obtained in this paper are much larger (0.516 in Model 3) than the aforementioned study in which the mean value of the estimated conditional environmental efficiency is 0.2933 with a high standard deviation (0.2339 compared to 0.164). This discrepancy, could be attributed to the different methodology applied since the former study uses a conditional directional distance function estimator extending the model of Kuosmanen (2005) ignoring the role of separability in the input-output analysis.

Next we perform various econometric techniques in order to model the relationship between the calculated environmental efficiencies and economic growth in attaining sustainability. In the first stage, we perform parametric regression analysis by estimating three cubic model specifications.

The results from our analysis are depicted in Table 3. Specifically, in two of the three estimated models, we find significant evidence consistent with an N-shaped relationship between environmental efficiency and regional economic growth. More specifically, the coefficients on the GDP terms (i.e. income, income squared and income cubed) in the first two models (Model 1 and 2) are statistically significant alternating their signs starting from positive to negative. This suggests the existence of N-shaped curve.

Table 2: Efficiency scores in each of the three models (2012)

State	Model 1 EFF (CO_2+SO_2+NO_X)	Model 2 EFF(SO_2+NO_X)	Model 3 EFF(CO_2)
AK	0.909	0.909	0.907
AL	0.125	0.163	0.548
AR	0.173	0.196	0.527
AZ	0.149	0.205	0.541
CA	0.075	0.097	0.306
CO	0.182	0.210	0.492
CT	0.123	0.193	0.511
DE	0.021	0.066	0.337
FL	0.072	0.143	0.419
GA	0.059	0.090	0.366
HI	0.849	0.867	1.000
IA	0.414	0.424	0.687
ID	0.371	0.366	0.379
IL	0.044	0.172	0.512
IN	0.213	0.260	0.581
KS	0.207	0.231	0.563
KY	0.176	0.203	0.571
LA	0.467	0.450	0.790
MA	0.103	0.167	0.509
MD	0.094	0.143	0.438
ME	0.188	0.259	0.500
MI	0.114	0.162	0.514
MN	0.164	0.195	0.397
MO	0.111	0.135	0.530
MS	0.154	0.167	0.463
MT	0.177	0.276	0.562
NC	0.092	0.133	0.363
ND	0.369	0.361	0.649
NE	0.243	0.259	0.576
NH	0.259	0.300	0.514
NJ	0.031	0.102	0.312
NM	0.498	0.533	0.730
NV	0.295	0.432	0.685
NY	0.107	0.155	0.360
OH	0.077	0.104	0.394
OK	0.139	0.162	0.459
OR	0.125	0.141	0.229
PA	0.117	0.179	0.504
RI	0.002	0.002	0.434
SC	0.122	0.190	0.545
SD	0.461	0.442	0.518
TN	0.045	0.102	0.367
TX	0.060	0.117	0.504
UT	0.634	0.725	0.824
VA	0.158	0.176	0.452
VT	0.219	0.217	0.254
WA	0.153	0.187	0.247
WI	0.240	0.267	0.586
WV	0.152	0.364	0.538
WY	0.561	0.682	0.821
Descriptives			
Mean	0.218	0.262	0.516
Stdev	0.198	0.195	0.164
Median	0.153	0.194	0.511
Max	0.909	0.909	1.000
Min	0.002	0.002	0.229
CV	0.907	0.744	0.317

However, for the CO_2 model, the individual estimates are not statistically significant although the pattern of alternating signs still holds. It is worth mentioning that the existence of non linear effects generated by a cubic and not a quadratic specification is justified under the likelihood ratio tests (LR) testing the restrictions that the extra polynomial terms (e.g. GDP^2 and GDP^3) are zero (H_0: $b_2 = b_3 = 0$). As it is evident in all of the three models, the LR tests, reject the null hypothesis under which the restricted model is nested to the unrestricted one (third degree polynomial model). Since we have an N-shaped curve, we have two estimated turning points representing an estimated peak and an estimated low (Kijima et al., 2010).

More specifically, the estimated peak in all of the three models range from 21,233 US dollars (in 2009 constant prices) to 42,549 US dollars, while the estimated low of the curve lies within the boundary of 59,956 to 82,627 US dollars. These values are on average in alignment with other studies such as Halkos and Tzeremes (2013a) who estimate a turning point equal to approximately 49,000 US dollars confirming however -by the implementation of non-parametric analysis- the existence of an inverted U-shaped curve. We must stress however, that our findings contradict the study of Millimet et al. (2003) who argue that an inverted U shaped curve is evident for the USA states despite the fact that a cubic specification model is prevailed in their parametric analysis. Their estimated peak equals to 8,657 US dollars (in 1987 price levels) for the full sample model (NO_x model) and becomes 10,570 US dollars (for the partial NO_x sample model) and 16,417 US dollars (for the partial SO_2 sample model) respectively.

The estimated equations in the cubic specifications appear to be well behaved to the diagnostic tests. In all three models according to Hausman test, we reject the null hypothesis of random effects at a very high significance level (p-value<1%), thus indicating the validity of the fixed effects estimator[11]. Moreover, the F-statistic of the joint significance of all the explanatory variables is rejected at the 1% level in all of the three models indicating the validity of the specified control variables. However, the Wooldridge F-tests for first order autocorrelation in the error term (W-T diagnostic test) denote existence of autocorrelation revealing that the error terms in all of the three models are not i.i.d., meaning that the errors display serial dependence.

Having estimated the cubic models and in order to account for possible endogeneity issues generated by the inclusion of income as dependent variable into our specifications, we utilise three dynamic DIF-GMM models. The results are also reported in Table 3 (Panel B). As it may be seen, the empirical evidence in favour of an N-shaped curve does not dramatically change when employing a dynamic panel analysis. More specifically, the income polynomial coefficients (i.e. GDP, GDP squared and GDP cubed) are statistically different from zero at the $p<0.01$ level of significance in the first two models and at the $p<0.05$ level of significance in the last model including only CO_2 emissions.

For all of the three models, b_1s and b_3s are positive while b_2s are negative (alternating signs) suggesting the existence of a stable N-shaped relationship between environmental efficiency and regional economic growth. Additionally, the lagged efficiency score indicators are in nearly all cases significant at the 1% level and their high magnitude implies the suitability of the dynamic panel data estimation. Regarding the magnitude of the estimated two turning points, it is noteworthy that they depict less variability compared to the cubic models. Moreover, the Sargan-Hansen test from the two-step homoscedastic estimate can not reject the null hypothesis in all of the three models. This means, that the over-identifying restrictions are valid and satisfy the orthogonality conditions (Arellano, 2003; Roodman, 2009).

[11] The results are available upon request.

In addition, according to the p-values of the Arellano–Bond test for autocorrelation it is evident that first-order autocorrelation in differences is allowed (AR1) since the idiosyncratic errors are serially correlated, whereas second-order autocorrelation is not (AR2). In this case, the error terms are independent over time allowing for the estimates to be consistent.

In the next step and in order to check for the robustness of the dynamic GMM analysis, we employ the SYS-GMM estimator that was designed to overcome some of the limitations of the DIF-GMM. The main reason for using the SYS-GMM estimator is that the latter increases efficiency in cases where the lagged levels of the regressor are poor instruments for the first-differenced regressors (Blundell and Bond, 2000). For all the above reasons, we re-estimate our three models and the results are reported in Table 3 (see Panel C). As it is evident, the results support the previous empirical findings in two out of three models (see Model 1 and Model 3) leading to the confirmation of an N-shaped curve. Surprisingly, when SO_2 and NO_X emissions are the only air pollutants in our econometric model, the N-shaped does not hold since the income polynomial coefficients come with the opposite sign sequence (i.e. from negative to positive and then to negative).

In order to avoid to assume a specific functional form for the regression relationships and to empirically test the validity of our findings, we adopt a nonparametric LPOLSM to capture the impact of regional income growth on environmental efficiency in the USA states over the scrutinised period. The graphical presentation of the non parametric estimation of g(.) in each of the three models (i.e. all gases included, only SO_2 and NO_X and finally only CO_2 emissions) along with the 95% confidence bands (CI) is portrayed in Figures 1a-1c. It is evident that the relationship between GDP/capita (expressed in natural logarithm) and environmental efficiency is nonlinear exhibiting a strong similar N-shaped pattern.

Table 3: Parametric regression results

Panel A - Cubic Specification			
Control variables	**Model 1** *Dependent variable: EFF (CO_2+SO_2+NO_X)*	**Model 2** *Dependent variable: EFF (SO_2+NO_X)*	**Model 3** *Dependent variable: EFF (CO_2)*
GDP	0.0001* (1.53)	0.00013* (1.41)	0.00007 (1.00)
GDP^2	-2.96E-09* (-1.56)	-2.66e-09* (-1.46)	-1.47e-09 (-1.02)
GDP^3	1.90e-14* (1.58)	1.73e-14* (1.49)	9.36e-15 (1.03)
Constant	-2.244*** (-2.74)	-1.865** (-2.35)	-0.650 (-0.94)
Diagnostics			
Observations	600	600	600
Shape of curve	N-shape	N-shape	N-shape
Estimated Peak	21,233	42,549	36,612
Estimated Low	82,627	59,956	68,089
F-test	11.26*** [0.00]	12.46*** [0.00]	16.18*** [0.00]
W-T	3.39* [0.07]	5.06** [0.03]	7.35*** [0.01]
LR	3.71** [0.06]	3.95*** [0.07]	3.02* [0.08]
Panel B - DIF-GMM Specification			
EFF (-1)	0.565***(11.28)	0.419*** (67.20)	0.242*** (4.70)
EFF (-2)	-0.094** (-2.03)	0.162*** (60.94)	0.031 (0.81)
GDP	0.0003*** (2.58)	0.0001*** (9.20)	0.00015** (1.90)
GDP^2	-5.65e-09*** (-2.62)	-2.30e-09*** (-9.57)	-3.15e-09** (-1.94)
GDP^3	3.59e-14*** (2.64)	1.42e-14*** (9.95)	2.07e-14** (2.00)
Constant	-4.538*** (-2.44)	-1.888*** (-8.23)	-2.112* (-1.54)
Diagnostics			
Observations	500	500	500
Shape of curve	N-shape	N-shape	N-shape
Estimated Peak	42,776	44,327	44,402
Estimated Low	62,145	63,654	57,047
Instruments	67	69	69
Sargan-Hansen test	46.25 [0.82]	48.98 [0.84]	45.07 [0.92]
AR(1)	-2.58*** [0.009]	-2.63*** [0.008]	-2.88*** [0.004]
AR(2)	0.51 [0.60]	-1.13 [0.26]	-1.60 [0.11]
Panel C - SYS-GMM Specification			
EFF (-1)	0.495*** (47.05)	0.534*** (89.58)	0.445*** (85.77)
EFF (-2)	0.122*** (71.33)	0.137*** (47.92)	-0.080*** (-42.75)
GDP	0.0002*** (25.85)	-0.00003*** (-2.55)	0.0002*** (14.69)
GDP^2	-4.23e-09*** (-29.38)	4.98e-10** (2.22)	-5.09e-09*** (-15.01)
GDP^3	2.86e-14*** (33.26)	-2.38e-15* (-1.70)	3.28e-14*** (15.40)
Constant	-3.019*** (-22.07)	0.648*** (3.28)	-3.790*** (-13.29)
Diagnostics			
Observations	550	550	550
Shape of curve	N-shape	Inverted N-shape	N-shape
Estimated Peak	39,323	95,498	26,366
Estimated Low	59,279	43,997	77,090
Instruments	80	80	80
Sargan-Hansen test	47.61 [0.98]	48.00 [0.97]	44.11 [0.98]
AR(1)	-2.92*** [0.00]	-2.54*** [0.01]	-2.90*** [0.00]
AR(2)	-0.05 [0.95]	0.54 [0.58]	0.04 [0.97]

Note: The use of the fixed effects is justified after a Hausman test for each of the three models. Robust z-statistics/t-statistics are in parentheses. The numbers in square brackets denote the p-values. LR denotes the Likelihood Ratio test for the presence of non-linear effects. W-T is the Wooldridge F-test for first order autocorrelation in the error term. AR(1) and AR(2) are tests for serial autocorrelation. Significant at ***1%, **5% and *10% respectively. The estimated peaks and lows are in US dollars at 2009 prices. To preserve space and for the sake of simplicity we do not report the estimates of the time dummies which are available by the authors on request. The lag selection was performed relying on AIC and SC criteria.

From the inspection of Figure 1a, we argue that there is an increasing nonparametric regression line up to a certain logged GDP level (10.5). This indicates that when regional income level increase up to that point regions' environmental efficiencies levels are also increasing (i.e. regions' environmental inefficiency decreases). However after that estimated peak ("turning point'') it is evident that the regression line slightly decreases up to a certain point (10.8) and increases henceforth. This means that within this closed interval, the logged GDP/capita has a negative impact on USA states environmental efficiency levels. Alternatively, the regions' environmental inefficiency levels are increasing. From the combined analysis of these findings, we argue that there is an N-shaped relationship between regional environmental efficiency and regions' logged GDP/capita levels. This pattern is also evident in the other two models (Figures 1b and 1c).

Figure 1a: Local polynomial smooth for Model 1

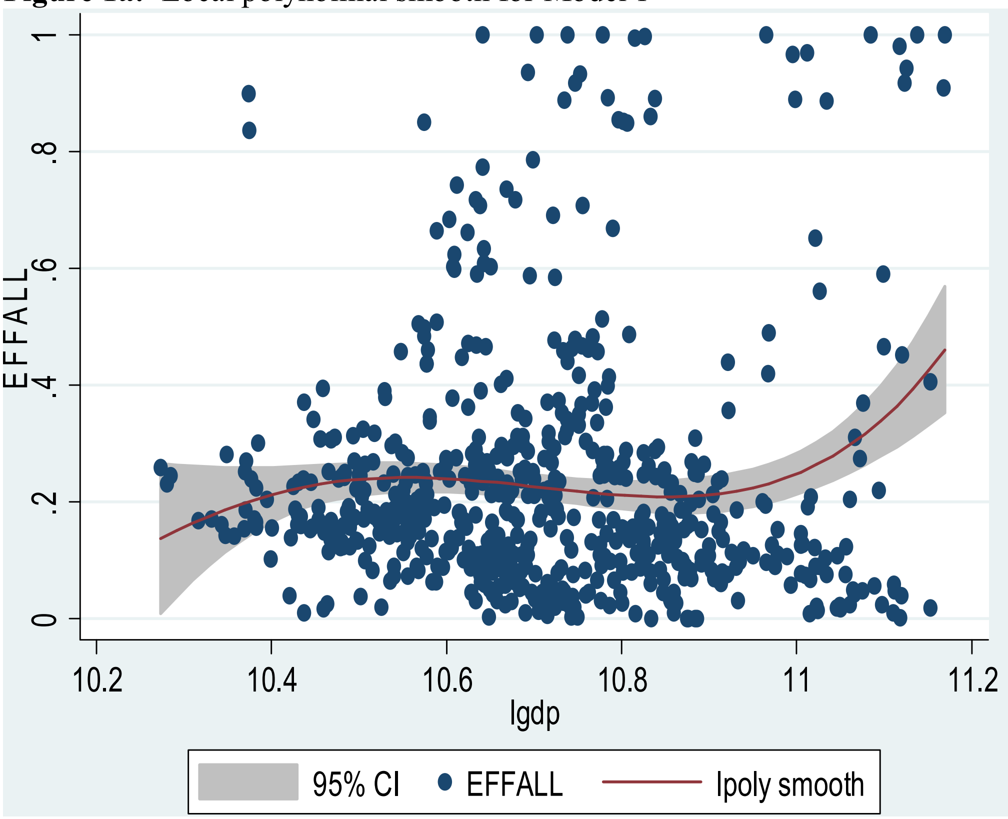


Figure 1b: Local polynomial smooth for Model 2

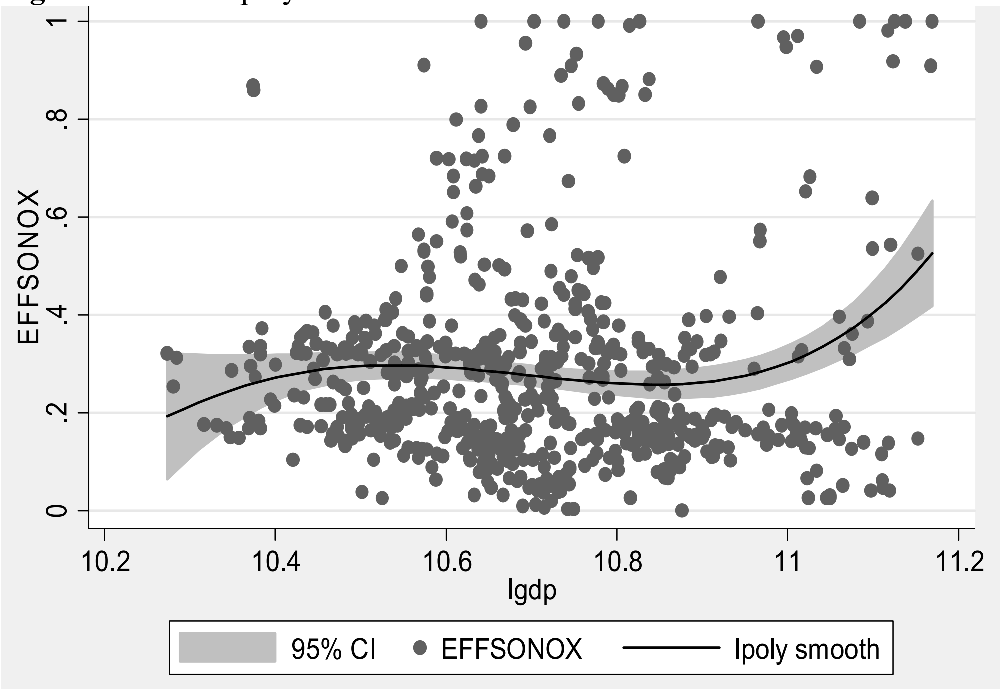
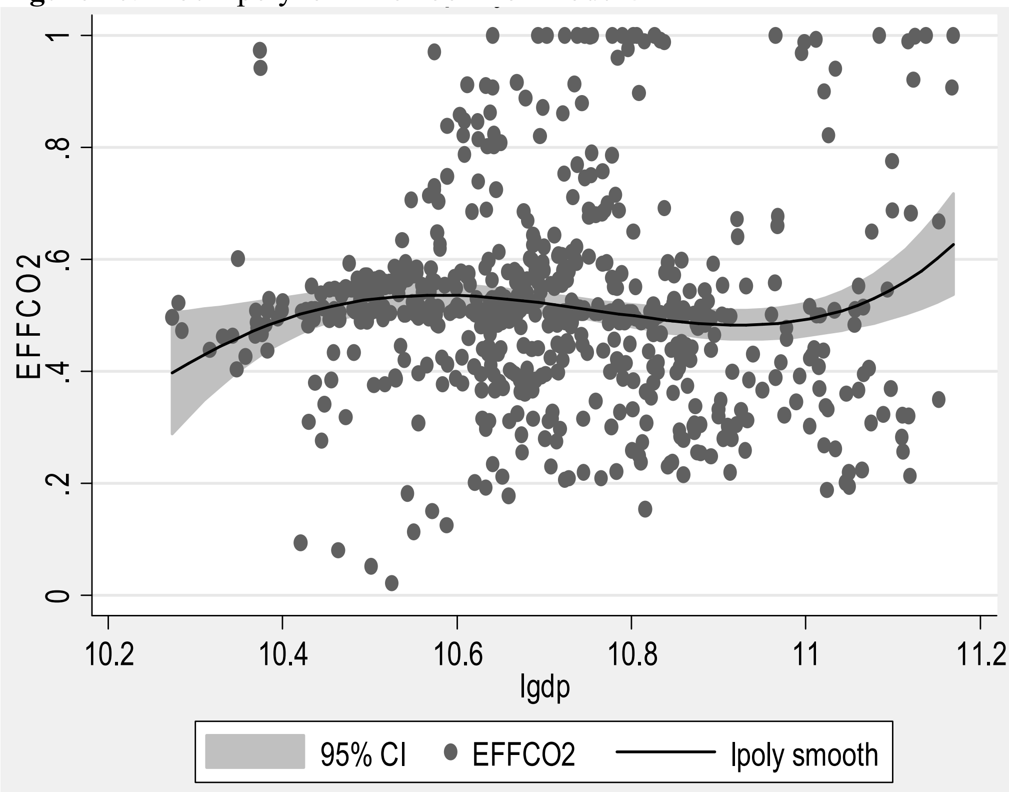


Figure 1c: Local polynomial smooth for Model 3



Note: In all figures solid lines denote the local polynomial estimated smooth, while the grey area depicts the 95% confidence bands.

4. Conclusions and policy implications

In our study the efficiency of the power generation sector in the USA states is estimated by integrating radial and non-radial efficiency measurements in a W-DEA framework. Specifically, using the proposed hybrid measure we consider first inputs and good and bad outputs as separable and non separable. Then we perform various parametric and non parametric econometric techniques to model the association between the extracted environmental efficiencies and economic growth in accomplishing sustainability. Economic growth is associated with higher levels of pollution. Our empirical results present initially an N-shape relationship between environmental efficiency (in all specifications) and regional economic growth.

The use of appropriate econometric methods in the second stage is important. In the presence of local (sulphur and nitrogen) and global (carbon) pollutants the estimated shapes of the curves differ. Specifically, in the case of local pollutants we extract an inverted N shape curve (only in SYS-GMM) while in the case of global pollutants an N-shape curve. When considering all pollutants together an N-shape curve is derived due to dominance of CO_2 emissions. This N-shape curve has the estimated peak at \$39323 and the estimated low at \$56279. Both calculated points are within the states considered with the maximum value being \$70918. This shows that the decline in environmental harm caused due to economic growth may be short-term and pollutants' emissions will be raised for an indefinite period above the income level of \$56279.

Lieb (2003) asserts that the declining part of the N-shape may be because of a shock while the increasing part because of an equilibrium association. According to Lieb the final upturn of this N-shape curve may be justified by the achievement of the internalization of the pollution externality on top of that the control chances are exhausted. He also states that there is lower thermodynamics bound on material and energy use per unit of GDP in addition to that at far above the ground incomes the abatement methods used show signs of decreasing and not any longer increasing returns to scale.

Considering the policy implications, one important inference is that in such analyses careful attention to pollutants examined is needed. Particularly pollutants should be analyzed according to their dispersion and regional dimension avoiding their simultaneous consideration in cases of calculating environmental efficiencies.

Moreover, different factors revealing states' investment policies may be used to measure continually the economic efficiency of states. Reforming their economic policies in order to cope with the total performance both in cross sectional (states) differences and time evolution may have an important potential effect on their economic efficiencies. For instance, in the case of the European Economic and Monetary Union enlargement, Halkos and Tzeremes (2009b) showed that it influenced differently the country members, with the old 15 EU members facing problems in economic efficiencies to reform economic policies coping with the EU enlargement.

Finally, environmental policies in firm level may be also considered. The application of Environmental Management Systems Standards (EMSS) has been promoted by policy makers due to various associated benefits from their implementation but some firms are reluctant to implement them. Evangelinos and Halkos (2002) test the significance of various factors in a firm's decision to implement EMSS. Specifically they consider whether a company implements EMSS if its management has a positive view of environmental issues, if there are pressures to progress its environmental attitude, if opportunities come up from its environmental actions and if it activates in sensitive environmental conditions.

Appendix

Table 1A: DEA efficiency scores for CO_2, SO_2, NO_X per USA state

Year	AK	AL	AR	AZ	CA	CO	CT	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS
2000	1.000	0.227	0.239	0.436	0.243	0.261	0.191	0.310	0.245	0.181	0.287	0.252	0.025	0.241	0.217	0.272	0.242	0.448	0.235	0.086	0.222	0.239	0.246	0.240	0.245
2001	0.889	0.233	0.270	0.436	0.169	0.284	0.208	0.274	0.246	0.154	0.312	0.252	0.039	0.243	0.239	0.274	0.250	0.469	0.239	0.082	0.264	0.244	0.245	0.232	0.258
2002	0.969	0.190	0.204	0.339	0.098	0.153	0.077	0.076	0.137	0.039	0.786	0.264	0.178	0.098	0.156	0.276	0.208	0.466	0.136	0.106	0.165	0.133	0.169	0.111	0.231
2003	0.967	0.150	0.160	0.182	0.008	0.112	0.067	0.049	0.121	0.034	0.888	0.269	0.234	0.079	0.139	0.263	0.174	0.352	0.118	0.044	0.247	0.117	0.151	0.103	0.167
2004	0.652	0.166	0.114	0.362	0.045	0.127	0.048	0.048	0.095	0.019	1.000	0.220	0.310	0.080	0.142	0.274	0.154	0.274	0.200	0.000	0.175	0.113	0.160	0.092	0.170
2005	0.887	0.187	0.123	0.110	0.069	0.144	0.056	0.059	0.111	0.038	0.995	0.352	0.325	0.067	0.097	0.242	0.190	0.303	0.153	0.026	0.203	0.126	0.186	0.090	0.161
2006	1.000	0.181	0.134	0.123	0.068	0.168	0.001	0.039	0.109	0.046	0.997	0.321	0.390	0.070	0.252	0.312	0.208	0.269	0.057	0.000	0.231	0.119	0.217	0.097	0.186
2007	0.943	0.141	0.123	0.135	0.079	0.232	0.018	0.024	0.109	0.037	0.891	0.288	0.379	0.082	0.211	0.267	0.219	0.367	0.008	0.000	0.196	0.112	0.254	0.100	0.171
2008	0.981	0.147	0.160	0.254	0.064	0.122	0.009	0.014	0.109	0.045	0.860	0.341	0.317	0.109	0.237	0.217	0.213	0.463	0.074	0.000	0.141	0.088	0.237	0.102	0.165
2009	1.000	0.132	0.169	0.150	0.029	0.133	0.023	0.016	0.089	0.050	0.892	0.304	0.308	0.087	0.181	0.210	0.173	0.707	0.110	0.000	0.089	0.082	0.154	0.090	0.142
2010	0.918	0.133	0.239	0.234	0.032	0.174	0.042	0.018	0.073	0.063	0.854	0.459	0.395	0.093	0.181	0.211	0.168	0.668	0.126	0.105	0.202	0.083	0.157	0.079	0.141
2011	1.000	0.170	0.157	0.162	0.010	0.161	0.076	0.022	0.064	0.063	0.852	0.417	0.341	0.084	0.184	0.211	0.200	0.917	0.122	0.105	0.182	0.090	0.178	0.093	0.281
2012	0.909	0.125	0.173	0.149	0.075	0.182	0.123	0.021	0.072	0.059	0.849	0.414	0.371	0.044	0.213	0.207	0.176	0.467	0.103	0.094	0.188	0.114	0.164	0.111	0.154
Diagnostics																									
Mean	0.932	0.168	0.174	0.236	0.076	0.173	0.072	0.075	0.122	0.064	0.805	0.319	0.278	0.106	0.188	0.249	0.198	0.475	0.129	0.050	0.193	0.128	0.194	0.118	0.190
Stdev	0.094	0.035	0.050	0.119	0.065	0.054	0.065	0.099	0.059	0.048	0.233	0.074	0.125	0.062	0.046	0.034	0.029	0.189	0.066	0.047	0.046	0.053	0.040	0.053	0.047
Median	0.967	0.166	0.160	0.182	0.068	0.161	0.056	0.039	0.109	0.046	0.860	0.304	0.317	0.084	0.184	0.263	0.200	0.463	0.122	0.044	0.196	0.114	0.178	0.100	0.170
Max	1.000	0.233	0.270	0.436	0.243	0.284	0.208	0.310	0.246	0.181	1.000	0.459	0.395	0.243	0.252	0.312	0.250	0.917	0.239	0.106	0.264	0.244	0.254	0.240	0.281
Min	0.652	0.125	0.114	0.110	0.008	0.112	0.001	0.014	0.064	0.019	0.287	0.220	0.025	0.044	0.097	0.207	0.154	0.269	0.008	0.000	0.089	0.082	0.151	0.079	0.141
CV	0.101	0.208	0.285	0.502	0.860	0.312	0.906	1.321	0.484	0.754	0.290	0.231	0.450	0.589	0.242	0.138	0.146	0.397	0.514	0.944	0.238	0.416	0.206	0.447	0.247

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.
Source: Authors' elaboration.

Table 1A: DEA efficiency scores for CO_2, SO_2, NO_X per USA state (continued).

Year	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY
2000	0.252	0.212	0.306	0.269	0.073	0.249	0.284	0.257	0.197	0.088	0.239	0.131	0.002	0.240	0.245	0.270	0.196	0.222	0.197	0.207	0.037	0.109	0.248	0.899	0.246
2001	0.300	0.214	0.313	0.278	0.024	0.248	0.276	0.259	0.212	0.076	0.251	0.167	0.081	1.000	0.246	0.268	0.236	0.225	0.213	0.206	0.019	0.133	0.248	0.836	0.269
2002	0.155	0.110	0.458	0.275	0.343	0.083	0.505	0.273	0.125	0.055	0.167	0.146	0.078	0.057	0.187	0.165	0.115	0.049	0.850	0.127	0.113	0.155	0.031	0.223	0.309
2003	0.175	0.092	0.624	0.292	0.477	0.076	0.665	0.247	0.107	0.029	0.159	0.120	0.009	1.000	0.163	0.390	0.101	0.032	0.345	0.080	0.063	0.136	0.169	0.156	0.179
2004	0.148	0.089	0.603	0.312	0.478	0.098	0.590	0.242	0.088	0.033	0.099	0.165	0.012	1.000	0.171	0.296	0.100	0.021	0.598	0.112	0.167	0.157	0.170	0.102	0.186
2005	0.169	0.060	0.717	0.332	0.483	0.108	0.471	0.264	0.089	0.045	0.184	0.143	0.005	0.933	0.159	0.411	0.097	0.020	0.608	0.105	0.178	0.153	0.190	0.139	0.194
2006	0.220	0.075	0.736	0.336	0.457	0.097	0.661	0.204	0.146	0.042	0.175	0.175	0.040	0.091	0.166	0.401	0.113	0.030	0.935	0.089	0.311	0.185	0.235	0.159	0.204
2007	0.302	0.051	0.588	0.280	0.391	0.420	0.743	0.214	0.127	0.038	0.171	0.173	0.028	0.041	0.188	0.309	0.086	0.027	0.691	0.099	0.283	0.165	0.188	0.188	0.220
2008	0.232	0.062	0.513	0.281	0.350	0.489	0.684	0.487	0.126	0.054	0.195	0.145	0.050	0.036	0.181	0.371	0.120	0.022	0.717	0.133	0.290	0.149	0.181	0.157	0.406
2009	0.192	0.063	0.362	0.281	0.441	0.439	0.507	0.239	0.106	0.030	0.173	0.132	0.034	0.585	0.135	0.317	0.106	0.044	0.774	0.128	0.378	0.152	0.178	0.010	0.452
2010	0.178	0.079	0.288	0.288	0.369	0.113	0.460	0.298	0.089	0.042	0.174	0.139	0.078	0.002	0.138	0.373	0.063	0.065	0.707	0.096	0.234	0.163	0.251	0.017	0.466
2011	0.297	0.081	0.356	0.294	0.109	0.060	0.484	0.257	0.090	0.052	0.190	0.146	0.139	0.021	0.183	0.399	0.137	0.065	0.603	0.137	0.232	0.159	0.274	0.245	0.590
2012	0.177	0.092	0.369	0.243	0.259	0.031	0.498	0.295	0.107	0.077	0.139	0.125	0.117	0.002	0.122	0.461	0.045	0.060	0.634	0.158	0.219	0.153	0.240	0.152	0.561
Diagnostics																									
Mean	0.215	0.098	0.479	0.289	0.327	0.193	0.525	0.272	0.124	0.051	0.178	0.147	0.052	0.385	0.176	0.341	0.117	0.068	0.606	0.129	0.194	0.151	0.200	0.253	0.329
Stdev	0.057	0.053	0.160	0.025	0.162	0.160	0.143	0.070	0.040	0.019	0.039	0.018	0.044	0.443	0.037	0.079	0.051	0.071	0.227	0.041	0.111	0.018	0.063	0.281	0.148
Median	0.192	0.081	0.458	0.281	0.369	0.108	0.505	0.257	0.107	0.045	0.174	0.145	0.040	0.091	0.171	0.371	0.106	0.044	0.634	0.127	0.219	0.153	0.190	0.157	0.269
Max	0.302	0.214	0.736	0.336	0.483	0.489	0.743	0.487	0.212	0.088	0.251	0.175	0.139	1.000	0.246	0.461	0.236	0.225	0.935	0.207	0.378	0.185	0.274	0.899	0.590
Min	0.148	0.051	0.288	0.243	0.024	0.031	0.276	0.204	0.088	0.029	0.099	0.120	0.002	0.002	0.122	0.165	0.045	0.020	0.197	0.080	0.019	0.109	0.031	0.010	0.179
CV	0.263	0.541	0.334	0.087	0.495	0.829	0.272	0.257	0.325	0.373	0.217	0.124	0.849	1.150	0.212	0.233	0.436	1.046	0.374	0.315	0.573	0.120	0.313	1.114	0.448

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.

Source: Authors' elaboration.

Table 2A: DEA efficiency scores for SO_2, NO_X per USA state

Year	AK	AL	AR	AZ	CA	CO	CT	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS
2000	1.000	0.323	0.273	0.439	0.324	0.331	0.315	0.331	0.326	0.264	0.377	0.334	0.217	0.319	0.301	0.341	0.321	0.519	0.320	0.305	0.319	0.313	0.333	0.310	0.312
2001	0.947	0.321	0.295	0.443	0.228	0.353	0.327	0.309	0.328	0.253	0.398	0.335	0.103	0.323	0.322	0.342	0.330	0.471	0.325	0.309	0.344	0.320	0.332	0.300	0.322
2002	0.969	0.217	0.227	0.387	0.163	0.182	0.141	0.081	0.209	0.044	0.825	0.314	0.354	0.160	0.194	0.320	0.250	0.502	0.196	0.183	0.318	0.171	0.231	0.155	0.253
2003	0.967	0.157	0.174	0.244	0.026	0.135	0.143	0.051	0.180	0.036	0.889	0.311	0.289	0.139	0.167	0.303	0.201	0.433	0.180	0.122	0.336	0.141	0.201	0.150	0.176
2004	0.652	0.180	0.143	0.607	0.078	0.159	0.126	0.048	0.135	0.020	1.000	0.290	0.319	0.143	0.142	0.319	0.172	0.422	0.290	0.162	0.288	0.133	0.211	0.135	0.175
2005	0.906	0.188	0.133	0.203	0.111	0.174	0.140	0.062	0.164	0.054	0.992	0.369	0.352	0.128	0.100	0.267	0.214	0.448	0.206	0.080	0.335	0.147	0.238	0.124	0.167
2006	1.000	0.180	0.176	0.227	0.120	0.207	0.139	0.041	0.163	0.068	1.000	0.334	0.390	0.136	0.276	0.342	0.241	0.378	0.174	0.165	0.311	0.145	0.263	0.130	0.189
2007	1.000	0.140	0.147	0.195	0.133	0.299	0.147	0.040	0.155	0.055	0.881	0.301	0.411	0.158	0.236	0.272	0.279	0.521	0.147	0.154	0.287	0.133	0.302	0.124	0.183
2008	0.981	0.154	0.166	0.338	0.110	0.153	0.116	0.027	0.152	0.047	0.850	0.357	0.362	0.167	0.282	0.227	0.276	0.673	0.152	0.150	0.287	0.112	0.273	0.111	0.167
2009	1.000	0.143	0.172	0.188	0.067	0.162	0.146	0.027	0.127	0.058	0.873	0.313	0.308	0.138	0.189	0.227	0.188	0.832	0.152	0.000	0.302	0.104	0.176	0.101	0.149
2010	0.918	0.156	0.255	0.274	0.084	0.204	0.171	0.027	0.128	0.078	0.851	0.455	0.406	0.151	0.189	0.227	0.190	0.862	0.182	0.154	0.294	0.108	0.180	0.096	0.148
2011	1.000	0.196	0.172	0.207	0.066	0.186	0.166	0.031	0.146	0.080	0.849	0.422	0.341	0.166	0.206	0.229	0.220	0.909	0.169	0.152	0.280	0.116	0.203	0.125	0.287
2012	0.909	0.163	0.196	0.205	0.097	0.210	0.193	0.066	0.143	0.090	0.867	0.424	0.366	0.172	0.260	0.231	0.203	0.450	0.167	0.143	0.259	0.162	0.195	0.135	0.167
Diagnostics																									
Mean	0.942	0.194	0.195	0.304	0.124	0.212	0.175	0.088	0.181	0.088	0.819	0.351	0.324	0.177	0.220	0.281	0.237	0.571	0.205	0.160	0.305	0.162	0.241	0.154	0.207
Stdev	0.094	0.061	0.052	0.130	0.078	0.070	0.068	0.104	0.068	0.078	0.201	0.052	0.084	0.065	0.066	0.049	0.051	0.184	0.064	0.080	0.025	0.072	0.055	0.069	0.063
Median	0.969	0.180	0.174	0.244	0.110	0.186	0.146	0.048	0.155	0.058	0.867	0.334	0.352	0.158	0.206	0.272	0.220	0.502	0.180	0.154	0.302	0.141	0.231	0.130	0.176
Max	1.000	0.323	0.295	0.607	0.324	0.353	0.327	0.331	0.328	0.264	1.000	0.455	0.411	0.323	0.322	0.342	0.330	0.909	0.325	0.309	0.344	0.320	0.333	0.310	0.322
Min	0.652	0.140	0.133	0.188	0.026	0.135	0.116	0.027	0.127	0.020	0.377	0.290	0.103	0.128	0.100	0.227	0.172	0.378	0.147	0.000	0.259	0.104	0.176	0.096	0.148
CV	0.100	0.315	0.267	0.427	0.633	0.332	0.389	1.190	0.377	0.883	0.245	0.150	0.260	0.369	0.298	0.174	0.215	0.322	0.312	0.503	0.083	0.442	0.227	0.451	0.303

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.
Source: Authors' elaboration.

Table 2A: DEA efficiency scores for SO_2, NO_X per USA state (continued).

Year	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY
2000	0.334	0.306	0.378	0.343	0.313	0.331	0.362	0.338	0.316	0.289	0.322	0.302	0.082	0.316	0.320	0.373	0.294	0.304	0.265	0.271	0.037	0.324	0.326	0.869	0.345
2001	0.372	0.305	0.385	0.353	0.032	0.330	0.355	0.340	0.317	0.276	0.330	0.327	0.251	1.000	0.327	0.377	0.314	0.299	0.346	0.267	0.025	0.331	0.329	0.859	0.353
2002	0.298	0.132	0.499	0.299	0.430	0.158	0.564	0.344	0.172	0.085	0.263	0.175	0.105	0.288	0.212	0.527	0.149	0.139	0.911	0.157	0.113	0.186	0.325	0.335	0.390
2003	0.360	0.112	0.651	0.313	0.489	0.131	0.720	0.322	0.148	0.066	0.248	0.126	0.010	1.000	0.182	0.461	0.127	0.114	0.477	0.083	0.063	0.159	0.207	0.320	0.397
2004	0.333	0.103	0.590	0.315	0.478	0.170	0.663	0.317	0.128	0.052	0.192	0.173	0.013	1.000	0.175	0.358	0.115	0.088	0.684	0.114	0.166	0.178	0.223	0.214	0.396
2005	0.353	0.064	0.715	0.354	0.516	0.163	0.573	0.345	0.135	0.053	0.282	0.146	0.007	0.933	0.173	0.494	0.116	0.127	0.686	0.105	0.175	0.170	0.239	0.236	0.403
2006	0.388	0.084	0.724	0.370	0.497	0.156	0.719	0.293	0.198	0.049	0.271	0.182	0.052	0.146	0.204	0.501	0.138	0.117	0.955	0.088	0.311	0.205	0.265	0.230	0.396
2007	0.433	0.052	0.572	0.279	0.391	0.551	0.798	0.292	0.175	0.047	0.230	0.178	0.039	0.145	0.185	0.324	0.106	0.101	0.766	0.098	0.283	0.194	0.209	0.336	0.387
2008	0.390	0.089	0.517	0.274	0.412	0.574	0.717	0.724	0.169	0.068	0.253	0.164	0.068	0.037	0.186	0.387	0.140	0.074	0.789	0.137	0.290	0.185	0.204	0.269	0.524
2009	0.325	0.096	0.425	0.275	0.441	0.477	0.549	0.345	0.144	0.032	0.217	0.154	0.040	0.585	0.157	0.312	0.125	0.092	0.827	0.133	0.378	0.181	0.192	0.170	0.543
2010	0.305	0.125	0.330	0.286	0.407	0.192	0.498	0.390	0.127	0.047	0.216	0.170	0.108	0.003	0.171	0.358	0.088	0.104	0.766	0.102	0.234	0.188	0.263	0.216	0.536
2011	0.406	0.131	0.347	0.293	0.153	0.112	0.529	0.384	0.129	0.060	0.240	0.156	0.197	0.076	0.219	0.386	0.208	0.107	0.684	0.152	0.232	0.184	0.293	0.333	0.639
2012	0.276	0.133	0.361	0.259	0.300	0.102	0.533	0.432	0.155	0.104	0.162	0.141	0.179	0.002	0.190	0.442	0.102	0.117	0.725	0.176	0.217	0.187	0.267	0.364	0.682
Diagnostics																									
Mean	0.352	0.133	0.500	0.309	0.374	0.265	0.583	0.374	0.178	0.094	0.248	0.184	0.089	0.425	0.208	0.408	0.156	0.137	0.683	0.145	0.194	0.206	0.257	0.365	0.461
Stdev	0.046	0.081	0.141	0.036	0.143	0.170	0.136	0.112	0.065	0.085	0.047	0.060	0.078	0.418	0.054	0.070	0.072	0.075	0.205	0.062	0.110	0.055	0.049	0.229	0.111
Median	0.353	0.112	0.499	0.299	0.412	0.170	0.564	0.344	0.155	0.060	0.248	0.170	0.068	0.288	0.186	0.386	0.127	0.114	0.725	0.133	0.217	0.186	0.263	0.320	0.397
Max	0.433	0.306	0.724	0.370	0.516	0.574	0.798	0.724	0.317	0.289	0.330	0.327	0.251	1.000	0.327	0.527	0.314	0.304	0.955	0.271	0.378	0.331	0.329	0.869	0.682
Min	0.276	0.052	0.330	0.259	0.032	0.102	0.355	0.292	0.127	0.032	0.162	0.126	0.007	0.002	0.157	0.312	0.088	0.074	0.265	0.083	0.025	0.159	0.192	0.170	0.345
CV	0.130	0.605	0.282	0.117	0.382	0.641	0.234	0.299	0.366	0.905	0.191	0.327	0.876	0.981	0.261	0.171	0.464	0.546	0.300	0.427	0.569	0.269	0.192	0.627	0.241

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.

Source: Authors' elaboration.

Table 3A: DEA efficiency scores for CO_2, per USA state

Year	AK	AL	AR	AZ	CA	CO	CT	DE	FL	GA	HI	IA	ID	IL	IN	KS	KY	LA	MA	MD	ME	MI	MN	MO	MS
2000	1.000	0.505	0.467	0.647	0.487	0.498	0.499	0.395	0.497	0.453	0.526	0.503	0.080	0.495	0.508	0.518	0.506	0.685	0.498	0.502	0.490	0.499	0.499	0.487	0.473
2001	0.987	0.506	0.477	0.646	0.485	0.519	0.499	0.406	0.499	0.445	0.540	0.502	0.094	0.497	0.508	0.515	0.506	0.688	0.498	0.503	0.507	0.500	0.496	0.480	0.497
2002	0.993	0.545	0.495	0.626	0.327	0.363	0.302	0.261	0.424	0.229	0.871	0.548	0.309	0.449	0.530	0.569	0.555	0.724	0.398	0.456	0.504	0.482	0.387	0.439	0.522
2003	0.968	0.549	0.481	0.555	0.154	0.307	0.369	0.223	0.425	0.274	0.914	0.562	0.276	0.486	0.537	0.584	0.550	0.669	0.430	0.505	0.503	0.519	0.353	0.488	0.437
2004	0.900	0.560	0.492	0.814	0.237	0.379	0.308	0.256	0.443	0.205	1.000	0.548	0.318	0.500	0.563	0.599	0.558	0.644	0.500	0.467	0.501	0.523	0.361	0.509	0.462
2005	0.940	0.577	0.433	0.560	0.253	0.425	0.323	0.322	0.446	0.447	0.989	0.612	0.375	0.501	0.534	0.578	0.576	0.680	0.477	0.502	0.503	0.537	0.419	0.507	0.463
2006	1.000	0.573	0.571	0.563	0.280	0.500	0.320	0.213	0.441	0.517	1.000	0.595	0.390	0.502	0.601	0.625	0.583	0.649	0.392	0.482	0.501	0.532	0.437	0.526	0.487
2007	0.999	0.554	0.489	0.541	0.279	0.598	0.349	0.369	0.439	0.480	0.987	0.592	0.388	0.505	0.580	0.607	0.572	0.749	0.409	0.483	0.501	0.528	0.528	0.525	0.483
2008	0.989	0.552	0.514	0.613	0.296	0.407	0.283	0.188	0.432	0.391	0.992	0.623	0.376	0.507	0.598	0.581	0.573	0.879	0.441	0.500	0.501	0.508	0.521	0.527	0.436
2009	1.000	0.547	0.492	0.523	0.284	0.409	0.367	0.195	0.411	0.380	0.960	0.609	0.385	0.506	0.575	0.569	0.570	1.000	0.457	0.477	0.500	0.494	0.383	0.530	0.403
2010	0.920	0.538	0.593	0.585	0.294	0.486	0.514	0.202	0.396	0.411	0.977	0.711	0.433	0.508	0.575	0.560	0.559	1.000	0.516	0.495	0.500	0.495	0.399	0.517	0.427
2011	1.000	0.560	0.518	0.541	0.215	0.435	0.482	0.219	0.445	0.393	1.000	0.688	0.341	0.509	0.569	0.563	0.582	1.000	0.436	0.465	0.500	0.413	0.438	0.525	0.602
2012	0.907	0.548	0.527	0.541	0.306	0.492	0.511	0.337	0.419	0.366	1.000	0.687	0.379	0.512	0.581	0.563	0.571	0.790	0.509	0.438	0.500	0.514	0.397	0.530	0.463
Diagnostics																									
Mean	0.969	0.547	0.504	0.597	0.300	0.448	0.394	0.276	0.440	0.384	0.904	0.598	0.319	0.498	0.558	0.572	0.559	0.781	0.459	0.483	0.501	0.503	0.432	0.507	0.473
Stdev	0.039	0.021	0.042	0.078	0.094	0.077	0.091	0.080	0.030	0.095	0.169	0.067	0.111	0.016	0.032	0.031	0.025	0.140	0.044	0.021	0.004	0.032	0.061	0.027	0.050
Median	0.989	0.549	0.492	0.563	0.284	0.435	0.367	0.256	0.439	0.393	0.987	0.595	0.375	0.502	0.569	0.569	0.570	0.724	0.457	0.483	0.501	0.508	0.419	0.517	0.463
Max	1.000	0.577	0.593	0.814	0.487	0.598	0.514	0.406	0.499	0.517	1.000	0.711	0.433	0.512	0.601	0.625	0.583	1.000	0.516	0.505	0.507	0.537	0.528	0.530	0.602
Min	0.900	0.505	0.433	0.523	0.154	0.307	0.283	0.188	0.396	0.205	0.526	0.502	0.080	0.449	0.508	0.515	0.506	0.644	0.392	0.438	0.490	0.413	0.353	0.439	0.403
CV	0.040	0.039	0.084	0.130	0.313	0.173	0.231	0.288	0.067	0.248	0.187	0.112	0.348	0.033	0.057	0.054	0.045	0.179	0.096	0.044	0.008	0.063	0.140	0.053	0.105

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.
Source: Authors' elaboration.

Table 3A: DEA efficiency scores for CO_2 per USA state (continued).

Year	MT	NC	ND	NE	NH	NJ	NM	NV	NY	OH	OK	OR	PA	RI	SC	SD	TN	TX	UT	VA	VT	WA	WI	WV	WY
2000	0.507	0.487	0.535	0.504	0.511	0.497	0.523	0.505	0.498	0.500	0.494	0.308	0.495	0.500	0.505	0.498	0.481	0.491	0.517	0.436	0.051	0.415	0.502	0.974	0.974
2001	0.529	0.491	0.540	0.515	0.511	0.497	0.517	0.506	0.500	0.467	0.505	0.386	0.501	1.000	0.508	0.515	0.490	0.488	0.515	0.421	0.021	0.414	0.501	0.941	0.941
2002	0.525	0.402	0.706	0.534	0.580	0.348	0.714	0.567	0.331	0.311	0.538	0.181	0.478	0.394	0.529	0.506	0.387	0.506	0.970	0.399	0.113	0.259	0.493	0.507	0.507
2003	0.553	0.384	0.848	0.577	0.753	0.305	0.838	0.575	0.319	0.286	0.545	0.149	0.500	1.000	0.538	0.485	0.408	0.505	0.619	0.331	0.125	0.249	0.518	0.509	0.509
2004	0.547	0.384	0.821	0.600	0.746	0.385	0.802	0.572	0.258	0.280	0.517	0.211	0.481	1.000	0.558	0.399	0.440	0.503	0.787	0.467	0.201	0.272	0.504	0.509	0.509
2005	0.554	0.297	0.910	0.604	0.757	0.366	0.738	0.591	0.321	0.327	0.569	0.178	0.483	0.998	0.562	0.501	0.432	0.512	0.801	0.446	0.192	0.277	0.555	0.506	0.506
2006	0.564	0.315	0.916	0.594	0.699	0.389	0.846	0.524	0.422	0.314	0.562	0.209	0.502	0.300	0.572	0.523	0.495	0.506	1.000	0.337	0.311	0.291	0.579	0.510	0.510
2007	0.594	0.419	0.819	0.551	0.687	0.660	0.912	0.543	0.428	0.310	0.560	0.219	0.499	0.347	0.564	0.367	0.394	0.505	0.860	0.442	0.315	0.296	0.562	0.509	0.509
2008	0.586	0.398	0.786	0.548	0.675	0.677	0.857	0.896	0.415	0.315	0.568	0.221	0.486	0.526	0.559	0.449	0.510	0.486	0.888	0.509	0.297	0.302	0.555	0.513	0.513
2009	0.559	0.359	0.715	0.551	0.769	0.671	0.748	0.623	0.345	0.305	0.554	0.209	0.424	1.000	0.544	0.397	0.483	0.503	0.906	0.447	0.378	0.302	0.553	0.510	0.510
2010	0.567	0.404	0.691	0.551	0.683	0.330	0.703	0.644	0.331	0.370	0.548	0.237	0.508	0.464	0.544	0.444	0.376	0.503	0.861	0.373	0.234	0.305	0.594	0.510	0.510
2011	0.633	0.384	0.641	0.594	0.501	0.219	0.725	0.635	0.267	0.368	0.554	0.235	0.513	0.513	0.565	0.412	0.578	0.503	0.809	0.423	0.325	0.255	0.605	0.510	0.510
2012	0.562	0.363	0.649	0.576	0.514	0.312	0.730	0.685	0.360	0.394	0.459	0.229	0.504	0.434	0.545	0.518	0.367	0.504	0.824	0.452	0.254	0.247	0.586	0.538	0.538
Diagnostics																									
Mean	0.560	0.391	0.737	0.561	0.645	0.435	0.743	0.605	0.369	0.350	0.536	0.229	0.490	0.652	0.546	0.463	0.449	0.501	0.797	0.422	0.217	0.299	0.547	0.580	0.580
Stdev	0.032	0.055	0.126	0.032	0.106	0.153	0.118	0.103	0.078	0.068	0.033	0.060	0.023	0.293	0.021	0.054	0.063	0.008	0.155	0.051	0.112	0.055	0.039	0.168	0.168
Median	0.559	0.384	0.715	0.551	0.683	0.385	0.738	0.575	0.345	0.315	0.548	0.219	0.499	0.513	0.545	0.485	0.440	0.503	0.824	0.436	0.234	0.291	0.555	0.510	0.510
Max	0.633	0.491	0.916	0.604	0.769	0.677	0.912	0.896	0.500	0.500	0.569	0.386	0.513	1.000	0.572	0.523	0.578	0.512	1.000	0.509	0.378	0.415	0.605	0.974	0.974
Min	0.507	0.297	0.535	0.504	0.501	0.219	0.517	0.505	0.258	0.280	0.459	0.149	0.424	0.300	0.505	0.367	0.367	0.486	0.515	0.331	0.021	0.247	0.493	0.506	0.506
CV	0.058	0.142	0.171	0.058	0.164	0.351	0.159	0.170	0.212	0.195	0.062	0.264	0.046	0.449	0.039	0.117	0.140	0.015	0.195	0.120	0.516	0.185	0.071	0.289	0.289

Note: The table reports the mean efficiency scores by state over the period (2000–2012). The efficiency scores were estimated with the window data envelopment analysis (hybrid method) considering inputs and outputs as separable and non separable. The benchmark best practice frontier for DEA is efficiency equal to 1.000.
Source: Authors' elaboration.

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