Journal of Environmental Management 211 (2018) 334–346

Contents lists available at ScienceDirect

Journal of Environmental Management

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

Research article

The impact of economic growth on environmental efficiency of the electricity sector: A hybrid window DEA methodology for the USA

George E. Halkos [a], Michael L. Polemis [b, c, *]

[a] Laboratory of Operations Research, Department of Economics, University of Thessaly, Volos, Greece
[b] Department of Economics, University of Piraeus, Piraeus, Greece
[c] Hellenic Competition Commission, Athens, Greece

A R T I C L E   I N F O

Article history:
Received 12 October 2017
Received in revised form
22 January 2018
Accepted 23 January 2018

Keywords:
Efficiency
Electricity
Window DEA
N-shape
USA

A B S T R A C T

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 good and undesirable outputs as separable and non separable. Then in the second stage, we perform parametric and non-parametric econometric techniques in order to model the relationship between the calculated environmental efficiencies and economic growth in attaining sustainability. Our empirical findings indicate a stable 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 local pollutants. This implies that attention is required when considering local and global pollutants and the extracted environmental efficiency scores. A clear message to policy makers and government officials is that climate change which calls for economic, environmental and social concern should be analyzed according to its dispersion and regional dimension.
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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% (IEA, 2014) 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 connection between environmental efficiency and economic growth known as Environmental Kuznets Curve (EKC) hypothesis, ignoring the role of the electricity sector (Managi, 2006; Daraio and Simar, 2005; Millimet et al., 2003; Zarzoso and Morancho, 2004; 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; Vaninsky, 2006; Kounetas, 2015). However, during the recent years, there are some attempts from the academic scholars to evaluate the efficiency of electricity industry integrating their greenhouse gas emissions (see for example Li et al., 2016; Chen et al., 2017; Monastyrenko, 2017). These studies, apply variants of the Data Envelopment Analysis (hereafter DEA) in order to captivate possible spillover effects. Although we examine the same relationship, we apply a different methodology which combines a novel window DEA (W-DEA) approach and non-parametric panel data estimations.

DEA method can 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 (see for example Han et al., 2018; Frija et al., 2011; Sueyoshi, 1999; Larsson and Telle, 2008; Hoang and Alauddin, 2012; Halkos and Managi, 2017). In this study, we estimate the efficiency of the electricity sector through the methodology of a non-parametric "*mathematical*" approach (DEA), originally developed by Farrell (1957). The DEA, method given the data set, produces a frontier that is optimal, while it represents the maximum output available for any DMU in the study, for its given inputs (Webb, 2003). Given that the non-

* Corresponding author. Department of Economics, University of Piraeus, Piraeus, Greece.
E-mail addresses: halkos@econ.uth.gr (G.E. Halkos), mpolemis@unipi.gr (M.L. Polemis).

[1] EKC hypothesis implies a non linear relationship of an inverted 'U' type between environmental degradation and economic growth.

https://doi.org/10.1016/j.jenvman.2018.01.067
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parametric frontier estimation does not require the imposition of any specific production technology, this is a standard approach in studies of transition and emerging economies, where assumptions of competitive markets with cost-minimization may not be appropriate (Apergis and Polemis, 2016).

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 significance of modeling policies when calculating the association between emissions-income. Similarly to our study, they use USA state-level panel data on two air pollutants (NO_x and SO_2) in order to estimate several EKCs by comparing parametric and semi-parametric techniques. They argue in favor of the more flexible semiparametric approach confirming the hypothesis of an inverted U-shape between emissions and regional economic growth.

Other researchers (see for example Bruyn and Opschoor, 1997; Sengupta, 1997) claim that some indicators such as CO_2 emissions exhibit an N-shape, implying that the environmental damage starts rising again after a fall to a specific point. Lastly, in an interesting paper, Maddison, 2006 extents the notion of the EKC nexus by estimating a spatial panel data model of 135 OECD countries in order to capture the effect 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 affected by the per capita emissions of neighbor 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 objective of this study is to estimate the regional efficiency scores of the electricity sector in a large scale economy such as the USA by combining separable and non-separable inputs in the production process to generate good and undesirable outputs respectively. Based on these estimates, we attempt to draw sharp inferences about the shape of the EKC by utilizing parametric and non-parametric panel data techniques.

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 US regions (states). Second, it utilizes a W-DEA approach with certain innovations such as the radial and non-radial efficiency measurements and the treatment of inputs and outputs (good and undesirable) as separable and non-separable. Although there are few similar studies that take into account the time series or dynamics into DEA modeling (see for example Asmild et al., 2004; Halkos and Tzeremes, 2009; Tone and Tsutsui, 2010; Wang et al., 2013; Khalili-Damghani et al., 2015), our study is the first which uses W-DEA methodology along with parametric and non-parametric econometric techniques. In our empirical analysis and for this balanced panel data a dynamic analysis based window DEA is used. If instead a cross sectional based static DEA was used all adjustment to any shock takes place within the same time period in which this occurs. This is justified only if we have either an equilibrium relationship or if the adjustment processes are really very fast (Perman and Stern, 1999).

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 while reports some policy implications.

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 undesirable 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 transmission, 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 (Vaninsky, 2006).

In contrast, many studies (Färe et al., 1989a, b, 1996, 2004; Färe 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-Tadeo et al., 2012; Zhang et al., 2011) use the capital stock and since they do not have available data on a regional basis, they often incorporate 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 by taking into account its proxy variable (i.e. energy transmission) which varies across different power plants.

Moreover, we assume that the two inputs affect the good output in a separable way since neither energy transmission nor operating cost of a power plant are linked with its production process (net generation). In contrast, the production of the good output generates the 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

[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. For a piecewise linear approximation in DEA models see Cook and Zhu (2009).

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

[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.

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