Journal of Cleaner Production xxx (2015) 1–8

Contents lists available at ScienceDirect

Journal of Cleaner Production

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

Population, economic growth and regional environmental inefficiency: evidence from U.S. states

George E. Halkos [a, *], David I. Stern [b], Nickolaos G. Tzeremes [a]

[a] Laboratory of Operations Research, Department of Economics, University of Thessaly, Korai 43, 38333, Volos, Greece
[b] Crawford School of Public Policy, The Australian National University, 132 Lennox Crossing, Acton, ACT 2601, Australia

A R T I C L E I N F O

Article history:
Received 20 December 2014
Received in revised form
8 June 2015
Accepted 9 June 2015
Available online xxx

Keywords:
Regional environmental inefficiency
Directional distance function
Nonparametric regression
Air pollution

A B S T R A C T

We apply a conditional directional distance function allowing multiple exogenous factors to measure environmental performance. We evaluate the air pollution performance levels of U.S. states for the years 1998 and 2008. States' environmental inefficiency is determined by population size and GDP per capita (GDPPC). The overall results reveal that there is much variation in environmental inefficiencies among the U.S. states. A second stage nonparametric analysis indicates a nonlinear relationship between states' population size, GDPPC levels and states' environmental inefficiency levels. Our results indicate that environmental inefficiency on the whole decreases with increased population and income per capita but there are limits to this improvement and at high income and population levels the tendency may reverse.

1. Introduction

'Green growth', which tackles both environmental and development problems, is increasingly seen by policymakers (UNEP, 2009, 2011) as a way to address the perceived conflict (Isenhour and Feng, 2014; Jänicke, 2012) between environmental quality and economic development. In this approach, policymakers need to be able to evaluate the ability of an economy to shift towards more efficient and cleaner procedures and resource saving processes and products (Jänicke, 2012). As the OECD (2002) indicates, this can only be accomplished by evaluating the ability of the implemented policies of an economy or a region to break the link between environmental pressures and economic goods (known also as decoupling). As Wursthorn et al. (2011) show, decoupling indicators help the policymaker to measure the ability of an economy to expand without damaging the environment. Based on this framework, we develop environmental efficiency indicators that enable us to evaluate the ability of an economy or a region to decouple economic growth from environmental and ecological harm. As has been highlighted by Wang et al. (2013), we can have two kinds of decoupling – 'absolute' or 'relative'. Absolute decoupling occurs when economic growth results in stable or lower environmental pressures. Relative decoupling occurs when economic growth is associated with higher environmental pressures but the increase in economic output is significantly higher than the increase in environmental pressures in proportional terms so that the environmental intensity of output falls.

Environmental efficiency measures whether firms, regions, industries or other organizational units (called decision making units or DMUs) minimize emissions of pollutants given the available technology and the levels of other inputs such as capital and labor that they use (Huang et al., 2014; Wang et al., 2014; Wu et al., 2014). There are many studies that model environmental efficiency (e.g. Färe et al., 1989, 2006, 2007, 2010) but these studies generally do not attempt to account for exogenous factors (also known as environmental factors) that might explain the differences in efficiency across production or geographical units. Though the total level of pollution is the most relevant variable environmentally, in order to understand why pollution varies across countries and states we need to decompose the factors that drive pollution emissions (Stern, 2004). A key factor is environmental efficiency and its variation across regions.

In this paper, we apply a conditional directional distance function estimator in order to evaluate the effect of population size and GDP per capita (GDPPC) on U.S. states' environmental performance levels. We apply recent developments in conditional

* Corresponding author.
E-mail address: halkos@econ.uth.gr (G.E. Halkos).

http://dx.doi.org/10.1016/j.jclepro.2015.06.038

directional distance functions that allow for multiple exogenous factors to determine technical efficiency under constant returns to scale (Daraio and Simar, 2014) to the environmental efficiency case.

There is some relevant related research on differences in environmental performance across U.S. states. Several studies have estimated environmental Kuznets curves for the states of the U.S.A. (Carson et al., 1997; List and Gallet, 1999; Aldy, 2005; Auffhammer and Steinhauser, 2012). Matisoff (2008) carried out an empirical analysis of the factors affecting the adoption of energy efficiency programs across U.S. states, Fredriksson and Millimet (2002) investigate whether states' environmental policy is influenced by their neighbors' policies and Heckman (2012) analyses the impact of management quality, spending, problem severity, and political factors on states' control of NO_x emissions.

Färe et al. (1989) were the first to model the trade-off between environmental quality and economic development using a nonparametric distance function approach. They provide a framework for measuring environmental technology in a production function context that enables the development of environmental performance indicators. Their model treats pollutants as joint outputs of the production process and imposes strong and weak disposability conditions on inputs and outputs. Since then, several studies have tried to model the trade-off between economic growth and environmental quality using the distance function approach (among others Zaim and Taskin, 2000a, 2000b, 2000c; Taskin and Zaim, 2001; Zaim, 2004; Managi, 2006; Yörük and Zaim, 2006; Managi and Jena, 2008). Most studies use country level data and normally involve the construction of measures of the environmental efficiency of the countries or regions first and then the effect of other variables on performance is assessed in a second stage regression type analysis.

However, as has been demonstrated by Simar and Wilson (2007, 2011), several unreasonable assumptions regarding the data generating process are needed in order for researchers to perform second-stage regressions using data envelopment analysis (hereafter DEA) efficiency scores as the dependent variable. In particular, most two-stage DEA studies assume that the separability condition between the input–output space and the space of the exogenous factors holds. Therefore, they assume that these factors (external/exogenous to the environmental production process) have no influence on the attainable set, affecting only the probability of being more or less efficient (Bădin et al., 2010, p.634). Finally, as reported by Daraio et al. (2010) the exogenous variables not only directly affect the shape of the distribution of the inefficiencies but also the production possibilities themselves.

Halkos and Tzeremes (2013a, 2013b) overcome these problems by applying the probabilistic characterization of directional distance functions firstly introduced by Simar and Vanhems (2012).[1] In this paper, following the recent developments introduced by (Daraio and Simar, 2014) we apply a conditional directional distance function (CDDF) approach to the multivariate case measuring the effect of both GDP per capita and population levels on U.S. states' environmental inefficiency levels. The paper is organized as follows: section two presents the data and the methodology adopted whereas section three presents the results obtained. The final section presents some conclusions.

[1] By imposing the weak disposability assumption on the outputs Halkos and Tzeremes (2013a, 2013b) applied a conditional directional distance function estimator that models the environmental performance-economic growth relationship under constant and variable returns to scale.

2. Data and methodology

2.1. Description of variables

Following several other studies (Färe et al., 1989; Zaim and Taskin, 2000a, 2000b, 2000c; Taskim and Zaim, 2001; Färe and Grosskopf, 2004; Zaim, 2004; Yörük and Zaim, 2006; Halkos and Tzeremes, 2009), we use a set of inputs and a set of bad and good outputs in order to define U.S. states' environmental production process. We use data for all 50 states of the U.S.A. for 1998 and 2008.[2] The set of inputs used are capital stock (in thousands of chained 2000 Dollars), energy use (in thousands of BTUs), and total state level employment. Furthermore, the good output is the real state GDP (in thousands of 2005 Dollars) and the bad outputs are carbon monoxide (CO), mono-nitrogen oxides (NO_X), and sulfur dioxide emissions (SO_2) measured in thousands of short tons (ST). The variables we use to explain the inefficiency levels are states' population levels (obtained from ratio of total and per capita GDP) and GDP per capita levels in constant 2005 Dollars. Both measures are also presented in thousands. Our data have been obtained from several sources. Specifically, states' total employment, real GDP, and GDP per capita have been obtained from the Bureau of Economic Analysis.[3] Total primary energy use is from the State Energy Data System (SEDS) provided by U.S. Energy Information Administration.[4] Data on air pollutants were obtained from the U.S. Environmental Protection Agency.[5] Finally, estimates of states' capital stock levels were obtained from Garofalo and Yamarik (2002) and Yamarik (2013). Table 1 provides some descriptive statistics for the variables used in our analysis.

2.2. Directional distance functions

In an environmental production process (Färe et al., 1989, 2004; Chung et al., 1997) let the input vector denoted by $x \in \Re_+^N$ be able to produce both a set of undesirable $u \in \Re_+^J$ and desirable $v \in \Re_+^M$ outputs. Then following Shephard (1970) and Färe and Primont (1995) the environmental technology can be defined given the following assumptions. Specifically, we assume that the output sets are closed and bounded and that inputs are freely disposable. Additionally, the environmental output set $P(x)$ can only be defined if:

1. $(v,u) \in P(x)$ and $0 \le \theta \le 1$ then $(\theta v, \theta u) \in P(x)$ (i.e. the outputs are weakly disposable) and
2. $(v,u) \in P(x)$, $u = 0$ implies that $v = 0$ (i.e. the null jointness assumption of good and bad outputs).

The assumption of weak disposability indicates that the reduction of bad outputs is costly and, therefore, it can only occur together with a simultaneous reduction in good outputs. Moreover, the assumption that the good outputs and bad outputs are null-joint implies that the bad outputs are by-products of the production process of good outputs.

Based on the weak disposability assumption for modeling undesirable outputs, a vast amount of research has been produced based on directional distance functions (among others Chung et al., 1997; Kuosmanen, 2005; Färe et al., 2006, 2007, 2010; Färe and

[2] We do not include the District of Columbia in our dataset since it is regarded as outlier in our analysis.

[3] The data can be downloaded from: http://www.bea.gov/regional/.

[4] The data can be downloaded from: http://www.eia.gov/beta/state/seds/seds-data-complete.cfm?sid=US.

[5] The data can be downloaded from: http://www.epa.gov/ttn/chief/index.html.