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Estimating the shadow prices of SO_2 and NO_x for U.S. coal power plants: A convex nonparametric least squares approach☆

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ABSTRACT

Weak disposability between outputs and pollutants, defined as a simultaneous proportional reduction of both outputs and pollutants, assumes that pollutants are byproducts of the output generation process and that a firm can "freely dispose" of both by scaling down production levels, leaving some inputs idle. Based on the production axioms of monotonicity, convexity and weak disposability, we formulate a convex nonparametric least squares (CNLS) quadratic optimization problem to estimate a frontier production function assuming either a deterministic disturbance term consisting only of inefficiency, or a composite disturbance term composed of both inefficiency and noise. The suggested methodology extends the stochastic semi-nonparametric envelopment of data (StoNED) described in Kuosmanen and Kortelainen (2011). Applying the method to estimate the shadow prices of SO_2 and NO_x generated by U.S. coal power plants, we conclude that the weak disposability StoNED method provides more consistent estimates of market prices.

1. Introduction

Coal power plants generate 47–56% of the electricity consumed in the U.S since 1989 (EIA, 2010). However, burning coal produces several byproduct pollutants, notably sulfur oxide (SO_2) and nitrogen oxide (NO_x), the major cause of acid rain. To address this problem, the Clean Air Act Amendments of 1990 (CAAA) set goals to reduce annual SO_2 emissions by 10 million tons and NO_x by 2 million tons from 1980 levels via a two-phase tightening of the restrictions placed primarily on coal plants (EPA, 2007). Phase I (1995–1999) regulated 445 boiler units at mostly coal plants and Phase II (2000–present) regulated over 2000 boiler units with a capacity greater than 25 MW at all fossil fuel plants. In 2011, the U.S. Environmental Protection Agency (EPA) released new environmental regulations requiring coal power plants to lower emissions of 84 toxic chemical levels within four years (EPA, 2011a).

An analysis of the effect of these regulations is helpful in understanding the impacts in terms of reductions in pollution and the associated costs for continued reductions. For this purpose we estimate a frontier production function, as first proposed by Farrell (1957). Data Envelopment Analysis (DEA), a technique named and popularized by Charnes et al. (1978), is extensively used to characterize firms' inputs usage to produce maximum level of outputs as well as to measure firms' technical efficiency. However, the original DEA model constructed a production frontier without modeling undesirable outputs such as pollutants. Consequently, Färe et al. (1986) extended DEA by applying Shephard's (1970) concept of weak disposability between desirable outputs and pollutants to estimate a production frontier and evaluate the impact of environmental regulations on technical efficiency. Today, the DEA weak disposability production frontier is applied to measure the firms' environmental performance. Färe et al. (1989) introduced a hyperbolic orientation to measure efficiency relative to DEA weak disposability frontier and applied the method to measure U.S. pulp and paper mills' technical efficiency and output losses due to environmental regulations. Yaisawarng and Klein (1994) measured productivity change of U.S. coal power plants by computing Malmquist input-based productivity assuming a DEA weak disposability frontier. Tyteca (1997) measured environment performance indicators of U.S. fossil fuel power plants based on a DEA weak disposability frontier. Pasurka (2006) calculated changes in SO_2 and NO_x associated with technical change, technical efficiency change and changes in input and output levels of U.S. coal power plants using an output distance function relative to a DEA weak disposability frontier. Mekaroonreung and Johnson (2010) used DEA and compared three approaches (hyperbolic efficiency measure; directional output distance function; linear transformation of pollutants)

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to estimate the technical efficiency of the U.S. oil refineries. See Zhou et al. (2008) for a summary of other DEA weak disposability applications in energy and environmental studies.

Recently, Sueyoshi and Goto (2011) proposed the concept of natural and managerial disposability and applied the concepts to a DEA frontier. A non-radial efficiency measure compared environmental performances and computed the returns to scale and damages to scale of national oil companies in several countries and international oil companies. This paper will focus on the more standard weak disposability assumption as the frontier for undesirable outputs implied by managerial disposability violates free disposability of inputs.

The implementation of the weak disposability assumption relative to a variable returns to scale (VRS) frontier has been subject to considerable debate. For instance, Färe and Grosskopf (2003) proposed a new model to construct a VRS weakly disposable production possibility set by introducing a single abatement factor across all firms whereas Kuosmanen (2005) used a non-uniform abatement factor across firms. In demonstrating that a production possibility set constructed by a single abatement factor model does not satisfy convexity, Kuosmanen and Podinovski (2008), proved that using non-uniform abatement factors allows the estimation of a VRS weakly disposable production possibility set that satisfies standard production axioms and the minimum extrapolation principle.

Many previous studies have estimated the shadow prices of undesirable outputs using distance functions. A ratio of the derivative of the distance function with respect to desirable output and the derivative of the distance function with respect to undesirable output characterizes the relative shadow price of the undesirable output, and parametric or nonparametric approaches can be used to estimate the distance function. The parametric approach is more widely used, because functions are everywhere differentiable. Färe et al. (1993) used an output distance function with the translog functional form to estimate a shadow price of four undesirable pollutants for 1976 data describing pulp and paper mills in Michigan and Wisconsin. Coggins and Swinton (1996) took the same approach to estimate the shadow price of SO_2 for Wisconsin coal plants in 1990–1992. Färe et al. (2005) used a quadratic directional output distance function to estimate both technical efficiency and a shadow price of SO_2 for the U.S. electric utilities in 1993 and 1997.

Despite its common usage, the parametric approach can be biased if the functional form is misspecified. Alternatively, a nonparametric approach, specifically DEA, can estimate a production frontier and the shadow prices of pollutants. Boyd et al. (1996) used a DEA production function to estimate the shadow price of SO_2 for coal plants. Lee et al. (2002) used DEA when accounting for technical inefficiency to derive the shadow prices of SO_2, NO_x and total suspend particulates (TSP) for Korean coal- and oil-burning plants in 1990–1995. Researchers also acknowledge some major limitations of the alternative approach: greater sensitivity to outliers, and the use of only a few observations to construct the production frontier. Moreover, DEA as a deterministic method does not incorporate statistical noise, and thus the observations of the production units must be observed without error and the production model specified without omitting any inputs or outputs.

Such drawbacks motivated the development of other nonparametric methods such as Convex Nonparametric Least Squares (CNLS), Kuosmanen (2006, 2008), which uses all available data to estimate a piecewise linear production function satisfying production axioms such as continuity, monotonicity and concavity. Kuosmanen and Johnson (2010) have shown that DEA is a special case of CNLS with sign constraints on error terms. To decompose statistical noise and inefficiency for cross-sectional data in a semi-parametric fashion, Kuosmanen and Kortelainen (2011) have proposed a two-stage method called Stochastic Non-parametric Envelopment of Data (StoNED).[1] It applies CNLS in the first stage to estimate an average production function and estimates the conditional expectation of inefficiency based on the CNLS residuals in the second stage.

The advantages of CNLS and StoNED over DEA motivated us to apply them to estimate a weak disposability production frontier. While DEA with weak disposability is well studied, to the best of our knowledge we are unaware of research that incorporates weak disposability with CNLS and StoNED. We describe our proposed model and apply it to measure the technical efficiency and to jointly estimate the shadow prices of SO_2 and NO_x for 196 U.S. coal power plants during Phase II of CAAA. To our knowledge there are no studies on the productive performance and shadow prices of SO_2 and NO_x using the U.S. coal power plants during Phase II of CAAA. The paper is organized as follows: the next section describes a nonparametric method of estimating a production function under weak disposability and the associated technical efficiency and shadow prices of SO_2 and NO_x. Section 3 describes the data set of 336 boilers of the U.S. bituminous coal power plants in operation from 2000 to 2008. Section 4 presents the analysis and discusses the results and Section 5 summarizes the conclusions.

2. Model

2.1. A production possibility set assuming weak disposability

For each firm $i=1\ldots, n$ let $x\in R_+^M$ be a vector of inputs, $y\in R_+^S$ be a vector of good outputs and $b\in R_+^J$ be a vector of bad outputs. The production possibility set is defined as $T=\{(x,y,b):x \text{ can produce } (y,b)\}$. The assumptions defining the production possibility set are:

1. T is convex
2. There are variable returns to scale

Originally proposed by Shephard (1970), the following axioms regarding production are restated when undesirable outputs are also produced:

3. Free disposability of inputs
   If $(x,y,b)\in T$ and $x^{'}\geq x$, then $\left(x^{'},y,b\right)\in T$.

4. Free disposability of outputs
   If $(x,y,b)\in T$ and $y^{'}\leq y$, then $\left(x,y^{'},b\right)\in T$.

5. Weak disposability between outputs and pollutants
   If $(x,y,b)\in T$ and $0\leq\varphi\leq 1$, then $(x,\varphi y,\varphi b)\in T$.

Based on the production possibility axioms stated above, the variable returns to scale weakly disposable production possibility set T can be written as:

$$T=\left\{(x,y,b)\in R_+^{M+S+J}\middle| x\geq\sum_{i=1}^{n}(\lambda_i+\mu_i)x_i; y\leq\sum_{i=1}^{n}\lambda_i y_i;\right.$$
$$\left. b\geq\sum_{i=1}^{n}\lambda_i b_i;\sum_{i=1}^{n}(\lambda_i+\mu_i)=1,\qquad \lambda_i,\mu_i\geq 0\right\} \tag{1}$$

where $\lambda_i s$ allows the convex combination of observed firms and $\mu_i s$ allows firms to scale down both outputs and pollutants while maintaining the same level of inputs.

Formulation (1) differs from the Kuosmanen (2005) formulation in that the inequality sign in the pollutant constraints implies a negative shadow price on additional pollution and satisfies the economic intuition that pollutants incur costs to firms.

[1] See Johnson and Kuosmanen (2011) or http://www.nomepre.net/stoned/ for further discussion of this naming.