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The production inefficiency of US electricity industry in the face of restructuring and emission reduction

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Abstract

Purpose – The paper investigates the production inefficiency of the US electricity industry in the wake of restructuring and emission reduction regulations.

Design/methodology/approach – The study estimates a multiple-input, multiple-output directional distance function, using six inputs: fuel, labor, capital and annualized capital costs of sulfur dioxide (SO_2), nitrogen oxides (NO_X) and particulate removal devices, two good outputs – residential and industrial-commercial electricity and three bad outputs – SO_2, carbon dioxide (CO_2) and NO_X emissions.

Findings – The authors find that restructuring in electricity markets improves deregulated utilities' technical efficiency (TE). Deregulated utilities with below-average NO_X control equipment tend to invest less in these devices, but above-average utilities do the opposite. The reverse applies to particulate removal devices. The whole sample spends more on NO_X, particulate and SO_2 control systems and reduces its electricity sales slightly. Increased investments in SO_2 and NO_X control equipment do not reduce SO_2 and NO_X emissions, but expansions of particulate control systems cut down SO_2 emissions greatly. Stricter environmental regulations have probably shifted the production frontier inwards and the utilities farther from the frontier over time.

Practical implications – Restructuring and environmental regulations do not make all utilities invest more in emission control systems. The US government should devise other schemes to achieve this goal.

Originality/value – The paper unveils heterogeneous reactions of US electric utilities in the wake of restructuring and emission regulations.

Keywords Technical inefficiency, Electricity industry, Restructuring, Emissions

Paper type Research paper

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1. Introduction

Emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_X) from electric generating units (EGUs) and other significant combustion sources contribute to the formation of ozone. High concentration of ozone at ground level can exacerbate respiratory diseases and raise susceptibility to respiratory infections. It can also damage sensitive vegetation, causing loss of diversity that may reduce the value of real property (US EPA, 2022). Severe health and ecological hazards of air pollution have brought about remarkable changes in environmental regulations, which began with the Clean Air Act Amendments of 1990 (Aldy *et al.*, 2022). Accordingly, several programs have been established to require power utilities to reduce SO_2 and NO_X emissions through cap-and-trade (CAT) systems. These programs set a cap on regional emissions and provide individual emission sources with flexibility in their compliance with emission limits.

It has long been recognized that this approach could effectively coordinate pollution abatement activities (Cicala, 2022). Fowlie (2010) argued that preexisting distortions in output markets might hinder the CAT programs from operating efficiently. Restructuring in electricity markets could induce deregulated plants to choose less capital-intensive control technology compared to regulated or publicly owned plants. Since regulated utilities enjoy a guaranteed rate of return on capital investment, they tend to overcapitalize their control devices relatively. Fowlie (2010) assumed that plant managers would choose a compliance strategy that minimizes a weighted sum of expected annual compliance costs and capital costs. There is, though, implied separability of emission control and electricity generation. It is more reasonable to expect that power plant managers would decide on an environmental compliance option based on not only its costs but also other indicators relevant to plant operation. This paper puts those managers' decisions in a broader view by examining production efficiency of US electric utilities in light of multiple inputs and multiple outputs.

To that end, we extend Fu's (2009) dataset by adding annualized capital costs spent on SO_2, NO_X and particulate removal devices. We employ a multiple-input, multiple-output directional distance function [1]. It allows us to avoid assuming separability, which may exclude statistically significant interactions among various outputs, and to compute the partial effects between any pair of endogenous variables. We find that restructuring in electricity markets tends to improve technical efficiency (TE) of deregulated utilities since they operate under the discipline of competitive markets. The absence of rate-of-return regulation will likely decrease capital investment in NO_X control equipment only for utilities that have this equipment below average but increase for utilities that have this equipment above average. The reverse applies to particulate removal devices. However, the whole sample spends more on these two as well as SO_2 control systems and reduces its electricity sales slightly.

There are several important interactions between inputs and outputs. Increased capital investments in SO_2 and NO_X control equipment do not reduce SO_2 and NO_X emissions, respectively. However, expansions in particulate control systems cut down SO_2 emissions greatly. Moreover, larger installations of NO_X and particulate removal devices help curb CO_2 emissions marginally. While residential and industrial-commercial electricity sales are substitutable, SO_2, CO_2 and NO_X emissions are generally complementary. Additionally, the utilities have been shifted increasingly farther from the frontier over time. Inward shifting of the production frontier, as well as declining TE and productivity growth, appears to follow the implementation of stricter environmental regulations.

The remainder of the paper is organized as follows. The next section presents the directional distance function's properties and productivity change computation (PC). Section 3 reports empirical results and conclusions followed in section 4.

2. The directional distance function

This section follows Agee *et al.* (2010). Consider a production technology in which electric utilities combine N nonnegative good inputs, $\mathbf{x} = (x_1, \ldots, x_N)' \in R_+^N$, to produce M nonnegative good outputs, $\mathbf{y} = (y_1, \ldots, y_M)' \in R_+^M$. A utility's production technology, S(x, y), is given by

$$\mathrm{S(x,\ y)} = \{(\mathrm{x},\ \mathrm{y}) : \mathbf{x} \text{ can produce } \mathbf{y}\}, \tag{1}$$

where S(x, y) consists of all feasible good input and good output vectors. We can extend (1) to include "bad" outputs (e.g., SO_2, CO_2 and NO_X emissions). Let $\tilde{\mathbf{y}} = (\tilde{y}_1, \ldots, \tilde{y}_L)' \in R_+^L$ denote a vector of L bad outputs produced jointly with y. Following Chambers *et al.* (1998), the output directional distance function is defined as

$$\vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) = \sup\left\{\beta : (\mathbf{y} + \beta\mathbf{g}_y, \tilde{\mathbf{y}} - \beta\mathbf{g}_{\tilde{y}}) \in P(\mathbf{x})\right\}, \tag{2}$$

where P(x) is the set of good and bad outputs that can be produced with inputs x and output direction $(\mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \neq (\mathbf{0}, \mathbf{0})$. For a given level of inputs, the output directional distance function measures the increase in good outputs (decrease in bad outputs) in the direction $\mathbf{g}_y(-\mathbf{g}_{\tilde{y}})$ in order to move to the frontier of P. Differences between the best practice (frontier), and actual outputs are measures of technical inefficiency in a utility's electricity generation. The measure is equal to zero when the utility is on the frontier of P and greater than zero when the utility is below the frontier of P.

The output directional distance function has the following properties:

D1. Translation property:

$$\vec{D}_0(\mathbf{x}, \mathbf{y} + \delta\mathbf{g}_y, \tilde{\mathbf{y}} - \delta\mathbf{g}_{\tilde{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) = \vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) - \delta, \tag{3}$$

D2. g-Homogeneity of degree minus one:

$$\vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \gamma\mathbf{g}_y, -\gamma\mathbf{g}_{\tilde{y}}) = \gamma^{-1}\vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}), \quad \gamma > 0, \tag{4}$$

D3. Good output monotonicity:

$$\mathbf{y}' \geq \mathbf{y} \Rightarrow \vec{D}_\tau(\mathbf{x}, \mathbf{y}', \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \leq \vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}), \tag{5}$$

D4. Bad output monotonicity:

$$\tilde{\mathbf{y}}' \geq \tilde{\mathbf{y}} \Rightarrow \vec{D}_\tau(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}'; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \geq \vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}), \tag{6}$$

D5. Concavity:

$$\vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \text{ is concave in } (\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}), \tag{7}$$

D6. Nonnegativity:

$$\vec{D}_0(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}; \mathbf{0}, \mathbf{g}_y, -\mathbf{g}_{\tilde{y}}) \geq 0 \Leftrightarrow (\mathbf{y}, \tilde{\mathbf{y}}) \in P(\mathbf{x}). \tag{8}$$

The translation property says that increasing $\boldsymbol{y}$ and decreasing $\tilde{\mathbf{y}}$ by δ-fold of their respective directions will reduce the directional distance by δ. Equation (4) implies that if each direction is scaled by γ; then the directional distance will be scaled by γ^{-1}. The following two expressions, (5) and (6) indicate that the directional distance function of a profit-maximizing utility is monotonically decreasing in good outputs and monotonically increasing in bad outputs. Expression (7) imposes concavity of the output directional distance function. In this paper, we impose D1, which will guarantee D2. We can test for D3 and D4. Normalization after estimation of the directional distance function is needed to make sure that D6 holds.

(1) *Quadratic output directional distance function.* We use a quadratic function to approximate the output directional distance function. In preliminary estimates, the null hypothesis that the squared input terms and the interaction terms among inputs are jointly equal to zero is rejected. We also reject the null hypotheses that the interaction terms between inputs and outputs are equal to zero and that the interaction terms between restructuring (RE) and annualized capital costs (KSO_2, KNOX, KTSP) spent on SO_2, NO_X and particulate removal devices are equal to zero. The quadratic form of the output directional distance function is as follows:

$$\begin{aligned}\vec{D}_{0,it}(\mathbf{x},\mathbf{y},\tilde{\mathbf{y}}) &= \gamma_i d_i + \sum_{n=1}^{N}\gamma_n x_{it,n} + \sum_{m=1}^{M}\gamma_m y_{it,m} + \sum_{l=1}^{L}\gamma_l \tilde{y}_{it,l} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n'=1}^{N}\gamma_{nn'}x_{it,n}x_{it,n'}\\ &+ \frac{1}{2}\sum_{m=1}^{M}\sum_{m'=1}^{M}\gamma_{mm'}y_{it,m}y_{it,m'} + \frac{1}{2}\sum_{l=1}^{L}\sum_{l'=1}^{L}\gamma_{ll'}\tilde{y}_{it,l}\tilde{y}_{it,l'} + \sum_{n=1}^{N}\sum_{m=1}^{M}\gamma_{nm}x_{it,n}y_{it,m}\\ &+ \sum_{n=1}^{N}\sum_{l=1}^{L}\gamma_{nl}x_{it,n}\tilde{y}_{it,l} + \sum_{m=1}^{M}\sum_{l=1}^{L}\gamma_{ml}y_{it,m}\tilde{y}_{it,l} + \gamma_t t + \gamma_{re}RE\\ &+ \gamma_{res}RE\times KSO2 + \gamma_{ren}RE\times KNOX + \gamma_{ret}RE\times KTSP + \varepsilon_{it},\end{aligned} \tag{9}$$

where d_i is a dummy variable for utility i, $i = 1, \ldots, F$ and

$$\varepsilon_{it} = \nu_{it} + \mu_{it}. \tag{10}$$

The composite error ε_{it} is an additive error with a one-sided component, $\mu_{it} \geq 0$, which captures technical inefficiency and statistical noise, ν_{it}, assumed to be iid with zero mean. We set the left-hand side of (9) equal to zero for all observations. To meet the translation property D1, we need to impose the following restrictions:

$$\begin{aligned}&\sum_{m=1}^{M}\gamma_m g_m - \sum_{l=1}^{L}\gamma_l g_l = -1,\\ &\sum_{m=1}^{M}\gamma_{mm'}g_m - \sum_{l=1}^{L}\gamma_{m'l}g_l = 0, \quad \forall m'\\ &\sum_{m=1}^{M}\gamma_{ml'}g_m - \sum_{l=1}^{L}\gamma_{ll'}g_l = 0, \quad \forall l'\\ &\sum_{m=1}^{M}\gamma_{nm}g_m - \sum_{l=1}^{L}\gamma_{nl}g_l = 0, \quad \forall n.\end{aligned} \tag{11}$$

Symmetry also is imposed on the doubly-subscripted coefficients in (9).

Again, following Agee *et al.* (2010), the fixed-effect approach is used here by including F utility-specific dummy variables to relax the strong distributional assumptions on both the ν_{it} and μ_{it}, and the unlikely assumption of no correlation between the μ_{it} and the explanatory variables that are required in the random-effect approach. The implicit function theorem allows us to examine the partial effect of any individual variable on another variable. For instance, the effect of a good output on another good output is $-(\partial \overrightarrow{D}_0/\partial y_m)/(\partial \overrightarrow{D}_0/\partial y_{m'})$, $\forall m, m'; m \neq m'$, and the effect of a bad output on another bad output is $-(\partial \overrightarrow{D}_0/\partial \tilde{y}_l)/(\partial \overrightarrow{D}_0/\partial \tilde{y}_{l'})$, $\forall l, l'; l \neq l'$. The effect of an input on another input is $-(\partial \overrightarrow{D}_0/\partial x_n)/(\partial \overrightarrow{D}_0/\partial x_{n'})$, $\forall n, n'; n \neq n'$. Finally, the effects of an input on a good output and a bad output are $-(\partial \overrightarrow{D}_0/\partial x_n)/(\partial \overrightarrow{D}_0/\partial y_m)$, $\forall m, n$, and $-(\partial \overrightarrow{D}_0/\partial x_n)/(\partial \overrightarrow{D}_0/\partial \tilde{y}_l)$, $\forall l, n$, respectively.

(2) *Measuring TE, EC, TC and PC.* This subsection follows Agee *et al.* (2010). Estimation of utility-specific TE, EC, TC and PC proceeds as follows. Since we want to measure EC, TC and PC in terms of percentage changes, we have to transform output directional distance function measures into Malmquist distance function measures. Following Balk *et al.* (2008), Malmquist output-oriented distance function measures in period t are

$$D_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) = 1/\left(1 + \overrightarrow{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})\right). \tag{12}$$

In the distance function,

$$1 = D_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})\exp(\epsilon_{it}), \tag{13}$$

$\epsilon_{it} = v_{it} + u_{it}$, which are assumed to be two-sided and one-sided error terms, respectively. Taking logs of (13) and using fitted values from (9) transformed by (12), we get

$$0 = \ln \widehat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \widehat{\epsilon}_{it}, \tag{14}$$

or

$$\widehat{\epsilon}_{it} = \widehat{v}_{it} + \widehat{u}_{it} = -\ln \widehat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}). \tag{15}$$

In order to sweep away the statistical noise, $\widehat{v}_{it}$, from the composite error, we follow Cornwell *et al.* (1990) by regressing $\widehat{\epsilon}_{it}$ on F utility dummies and the interactions of time with utility dummies:

$$\widehat{\epsilon}_{it} = \sum_{i=1}^{F} \psi_i d_i + \sum_{i=1}^{F} \phi_i d_i t + \zeta_{it}, \tag{16}$$

where the random error term ζ_{it} is uncorrelated with the regressors. The fitted values, $\tilde{u}_{it}$, of (16) are consistent estimates of u_{it}.

As u_{it} needs to be nonnegative, we transform $\tilde{u}_{it}$ by subtracting $\tilde{u}_t = \min_i(\tilde{u}_{it})$, which is the estimated frontier intercept, and obtain $\tilde{u}_{it}^F = \tilde{u}_{it} - \tilde{u}_t \geq 0$. Adding and subtracting $\tilde{u}_t$ from the estimated (14) yields

$$\begin{aligned} 0 &= \ln \widehat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \widehat{v}_{it} + \tilde{u}_{it} + \tilde{u}_t - \tilde{u}_t \\ &= \ln \widehat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \tilde{u}_t + \widehat{v}_{it} + \tilde{u}_{it} - \tilde{u}_t \\ &= \ln \widehat{D}_0^{F,t}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \widehat{v}_{it} + \tilde{u}_{it}^F, \end{aligned} \tag{17}$$

where $\ln \widehat{D}_0^{F,t}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) = \ln \widehat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \tilde{u}_t$ is the log of the fitted frontier shadow distance function in period t. Utility i's TE in period t is defined as

$$TE_{it} = \exp(-\tilde{u}_{it}^F). \tag{18}$$

$EC_{i,t+1}$ is the change in TE or the rate of catching up to the frontier from t to $t+1$, defined as

$$EC_{i,t+1} = TE_{i,t+1} - TE_{it}. \tag{19}$$

Technical change, $TC_{i,t+1}$, is estimated as the difference between $\ln \widehat{D}_0^{F,t+1}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})$ and $\ln \widehat{D}_0^{F,t}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})$, holding all inputs and outputs constant:

$$TC_{i,t+1} = \ln \widehat{D}_0^{t+1}(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}) + \tilde{u}_{t+1} - \left[\ln \widehat{D}_0^t(\mathbf{x}, \mathbf{y}, \tilde{\mathbf{y}}) + \tilde{u}_t\right]. \tag{20}$$

TC is interpreted as a shift in the frontier over time. Given $EC_{i,t}$ and $TC_{i,t}$, we obtain PC

$$PC_{it} = EC_{it} + TC_{it}. \tag{21}$$

(3) *Standardizing units.* As Agee *et al.* (2010) discussed, the output directional distance function involves inputs and outputs with different units. We cannot compare a certain absolute increase in kilowatt hours of electricity to an absolute decrease in tons of NO_X emissions. We need to standardize all input and output measures to a zero mean and unit variance, except for dichotomous variables. Then the marginal effect of a variable on another variable is in standard deviations.

(4) *Choosing direction.* Also, as discussed by Agee *et al.* (2010), the direction is not a parameter that can be estimated. Instead, we can assign the directions with a broad range of values expressing different assumed value judgments relevant to the tradeoffs between good and bad outputs.

3. Data and empirical results

3.1 Data

The dataset used in this paper is an extended version of the utilities panel initially analyzed by Fu (2009). The primary sources for Fu's data are the US Energy Information Administration's *Electric Power Annuals, Forms EIA-767, EIA-906, EIA-920* and the Federal Energy Regulatory Commission's *Forms FERC-1 and FERC-423*. The sample consists of 78 privately owned US utilities with fossil fuel-based electricity generation. The panel accommodates major changes in environmental regulations relevant to omission reductions such as the Acid Rain Program in 1995 and the wave of industry restructuring which began in 2001. During this period, 28 of these utilities stopped their steam electricity generation.

The outputs include two good outputs, residential and industrial-commercial electricity (SALR and SALIC), and three bad outputs (SO_2, CO_2 and NO_X emissions). The inputs initially are fuel, labor and capital. The quantity of fuel is the heat content from all fossil fuels burned. The quantities of labor and capital are defined as the ratios of input expenditures to prices.

We compile three new inputs, namely, annualized capital costs KSO2, KNOX and KTSP spent on SO_2, NO_X and particulate removal devices. Since control equipment can be used for several boilers in a power plant, we classify boilers into groups that share the same removal devices. Then we compute attributes of each group based on primary data for specific boilers from the US Energy Information Administration's *Forms EIA-767 and EIA-860*. These attributes are plugged into the Integrated Environmental Control Model (IECM) developed by the Department of Engineering and Public Policy at Carnegie Mellon University to obtain KSO2, KNOX and KTSP at group level. Finally, we aggregate them up to the utility level.

3.2 Empirical results

We standardize the data and estimate the directional distance function (9). Table 1 presents the function estimates corresponding to three alternative sets of direction vectors, following Agee *et al.* (2010). In column two with an output direction vector $(g_y, -g_{\tilde{y}}) = (2, -1)$, the translation property requires a two standardized unit increase in the good outputs for everyone standardized unit decrease in the bad outputs, holding all inputs constant, in order to move towards the frontier. In other words, $(g_y, -g_{\tilde{y}}) = (2, -1)$ weights a decrease in bad outputs twice as much as an increase in good outputs. We focus on the output direction vector $(g_y, -g_{\tilde{y}}) = (1, -1)$ shown in column three of Table 1 since we assume equal weights on increases in good outputs and reductions in bad outputs.

Before examining partial impacts among the outputs and inputs, we compute the partial derivatives of the directional distance function with respect to the outputs given in Table 2. They are averages weighted for electricity sales (including residential and industrial commercial) made by utilities [2]. The directional distance function is decreasing in the good outputs (i.e., residential and industrial-commercial electricity sales) and increasing in the bad outputs (i.e., SO_2, CO_2 and NO_X emissions). These results are consistent with the properties D3 and D4 stated above.

In addition, the directional distance function is decreasing with industry restructuring. This variable has an average partial effect of −0.0241. It implies that deregulated utilities are closer to the frontier in markets where electricity prices are no longer set by state regulators but are determined by competitive markets. The discipline of competitive markets improves their performance, as expected. However, the partial effect of restructuring on KNOX is different from Fowlie's (2010) findings (see Table 3). While below-average utilities (with KNOX below average) in deregulated markets tend to invest 20% less on NO_X control equipment, above-average utilities (with KNOX above average) tend to invest 50.7% more. The story for KTSP is the opposite. Restructuring induces below-average utilities to spend 2.66% more and above-average utilities to spend marginally 0.87% less on particulate control systems. However, for the whole sample, restructuring increases annualized capital costs for NO_X, particulate as well as SO_2 removal devices. Further, as a result of restructuring, these utilities reduce their residential and industrial-commercial electricity sales by 0.06 and 0.87%, respectively.

As power plants face more and more stringent environmental regulations on emissions, they have to switch to "greener" fuels or technologies, install more expensive removal devices, buy emission permits whose overall limits are decreasing, reduce plant utilization or even stop generation. Either compliance strategy means that they operate increasingly farther from the best-practice frontier than in the absence of these restraints. This is reflected by a positive and significant estimate of 0.010 for the time variable.

Variable	Coefficient (Standard error) $g_y = 2; -g_{\bar{y}} = -1$	$g_y = 1; -g_{\bar{y}} = -1$	$g_y = 1; -g_{\bar{y}} = -2$
Outputs			
SALIC	−0.17395	−0.28888	−0.24108
	(0.0137)**	(0.0247)**	(0.0205)**
SO_2	0.01217	0.02058	0.02410
	(0.0042)**	(0.0070)**	(0.0055)**
CO_2	0.08624	0.19067	0.17353
	(0.0076)**	(0.0115)**	(0.0084)**
NO_X	−0.01963	−0.03015	−0.01815
	(0.0053)**	(0.0089)**	(0.0071)**
$(SO_2)^2$	−0.00204	−0.00867	−0.01336
	(0.0041)	(0.0068)	(0.0054)**
$(CO_2)^2$	0.21482	0.24697	0.07436
	(0.0203)**	(0.0235)**	(0.01284)**
$(NO_X)^2$	0.00130	−0.00885	−0.01441
	(0.0047)	(0.0079)	(0.0063)**
SALR × SALIC	−0.13293	−0.13108	−0.04378
	(0.0143)**	(0.0283)**	(0.0249)*
SALIC × SO_2	0.02414	0.03557	0.02678
	(0.0074)**	(0.0127)**	(0.0104)**
SALIC × CO_2	−0.01422	−0.01168	−0.00274
	(0.0125)	(0.0189)	(0.0143)
SALIC × NO_X	0.01536	0.02051	0.01526
	(0.0073)**	(0.0128)	(0.0109)
$SO_2 \times CO_2$	−0.02352	−0.02773	−0.00232
	(0.0077)**	(0.0096)**	(0.0056)
$SO_2 \times NO_X$	−0.00361	−0.00484	−0.00402
	(0.0048)	(0.0080)	(0.0063)
$CO_2 \times NO_X$	−0.01630	−0.01573	0.00267
	(0.0094)*	(0.0118)	(0.0078)
Inputs			
FUEL	−0.03130	−0.07959	−0.08270
	(0.0082)**	(0.0133)**	(0.0102)**
LABOR	−0.01391	−0.02657	−0.02402
	(0.0041)**	(0.0069)**	(0.0055)**
CAPITAL	0.00895	0.01799	0.01385
	(0.0039)**	(0.0066)**	(0.0052)**
KSO2	0.01629	0.01393	0.00346
	(0.0102)	(0.0171)	(0.0136)
KNOX	−0.00563	−0.00888	−0.00108
	(0.0042)	(0.0070)	(0.0056)
KTSP	0.05820	0.10042	0.06261
	(0.0259)**	(0.0438)**	(0.0355)*
$FUEL^2$	0.08597	0.11243	0.05370
	(0.0150)**	(0.0227)**	(0.0165)**
$LABOR^2$	−0.00172	0.00170	0.00230
	(0.0031)	(0.0054)	(0.0043)
$CAPITAL^2$	−0.00723	−0.02098	−0.01951
	(0.0040)*	(0.0068)**	(0.0054)**

(*continued*)

Table 1.
Estimation results

Variable	Coefficient (Standard error) $g_y = 2; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -2$
$(KSO2)^2$	−0.00707 (0.0064)	−0.01450 (0.0108)	−0.01518 (0.0086)*
$KNOX^2$	0.02496 (0.0045)**	0.04114 (0.0076)**	0.02792 (0.0060)**
$KTSP^2$	−0.01195 (0.0093)	−0.01731 (0.0156)	−0.01179 (0.0124)
FUEL × LABOR	0.01077 (0.0055)*	0.01459 (0.0082)*	0.00289 (0.0058)
FUEL × CAPITAL	0.03782 (0.0063)**	0.04417 (0.0089)**	0.02509 (0.0063)**
FUEL × KSO2	0.02933 (0.0079)**	0.03543 (0.0125)**	0.01712 (0.0090)*
FUEL × KNOX	0.01737 (0.0078)**	0.02196 (0.0112)**	0.00102 (0.0074)
FUEL × KTSP	0.02974 (0.0084)**	0.02598 (0.0138)*	0.00303 (0.0106)
LABOR × CAPITAL	0.00024 (0.0029)	−0.00641 (0.0049)	−0.01090 (0.0039)**
LABOR × KSO2	0.02324 (0.0040)**	0.03663 (0.0066)**	0.02089 (0.0053)**
LABOR × KNOX	0.00027 (0.0020)	0.00236 (0.0035)	0.00217 (0.0029)
LABOR × KTSP	0.01078 (0.0027)**	0.00938 (0.0046)**	0.00191 (0.0037)
CAPITAL × KSO2	0.00838 (0.0035)**	0.01419 (0.0059)**	0.01436 (0.0047)**
CAPITAL × KNOX	−0.00671 (0.0027)**	−0.01021 (0.0046)**	−0.00505 (0.0037)
CAPITAL × KTSP	0.00210 (0.0036)	−0.00110 (0.0060)	−0.00065 (0.0048)
KNOX × KTSP	0.00844 (0.0047)*	0.01349 (0.0082)*	0.00285 (0.0067)
KNOX × KSO2	−0.01303 (0.0023)**	−0.02053 (0.0039)**	−0.01567 (0.0032)**
KTSP × KSO2	−0.00039 (0.0045)	0.00470 (0.0074)	0.00877 (0.0059)
Interaction terms among inputs and outputs			
FUEL × SALIC	−0.01399 (0.0141)	0.00513 (0.0214)	0.00193 (0.0154)
FUEL × SO_2	0.03721 (0.0098)**	0.06938 (0.0144)**	0.05167 (0.0098)**
FUEL × CO_2	−0.16882 (0.0157)**	−0.24292 (0.0207)**	−0.12721 (0.01313)**
FUEL × NO_X	0.01857 (0.0129)	0.03780 (0.0183)**	0.02536 (0.0123)**
LABOR × SALIC	0.00786 (0.0056)	0.01629 (0.0096)*	0.01560 (0.0079)*
LABOR × SO_2	−0.00364 (0.0029)	−0.01315 (0.0049)**	−0.01623 (0.0039)**

Table 1. (*continued*)

Variable	Coefficient (Standard error) $g_y = 2; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -2$
LABOR × CO_2	−0.00923	−0.00173	0.01360
	(0.0059)	(0.0083)	(0.0058)**
LABOR × NO_X	−0.00320	−0.00412	−0.00142
	(0.0036)	(0.0061)	(0.0049)
CAPITAL × SALIC	−0.02481	0.00539	−0.04658
	(0.0048)**	(0.0081)**	(0.0066)**
CAPITAL × SO_2	−0.00481	−0.00929	−0.01209
	(0.0036)	(0.0060)	(0.0048)**
CAPITAL × CO_2	−0.01031	0.00061	0.00669
	(0.0052)**	(0.0075)	(0.0057)
CAPITAL × NO_X	−0.00372	0.00368	0.00742
	(0.0038)	(0.0064)	(0.0050)
KSO2 × SALIC	−0.04275	−0.04927	−0.02403
	(0.0086)**	(0.0147)**	(0.0123)**
KSO2 × SO_2	−0.00105	−0.00229	−0.00256
	(0.0022)	(0.0037)	(0.0030)
KSO2 × CO_2	−0.01287	−0.00954	0.00213
	(0.0056)**	(0.0074)	(0.0045)
KSO2 × NO_X	−0.00302	−0.00705	−0.00840
	(0.0030)	(0.0051)	(0.0041)**
KNOX × SALIC	0.00525	0.00536	0.00525
	(0.0047)	(0.0084)	(0.0070)
KNOX × SO_2	0.00544	0.00766	0.00272
	(0.0032)*	(0.0054)	(0.0043)
KNOX × CO_2	−0.02991	−0.03509	−0.00986
	(0.0065)**	(0.0084)**	(0.0054)*
KNOX × NO_X	0.00650	0.00353	−0.00056
	(0.0032)**	(0.0054)	(0.0044)
KTSP × SALIC	0.00033	−0.02045	−0.00938
	(0.0131)	(0.0226)	(0.0190)
KTSP × SO_2	−0.00770	0.00395	0.01697
	(0.0061)	(0.0100)	(0.0075)**
KTSP × CO_2	−0.00842	−0.01448	−0.01381
	(0.0062)	(0.0096)	(0.0072)*
KTSP × NO_X	−0.00205	−0.00150	0.00037
	(0.0037)	(0.0064)	(0.0051)
Time			
TIME	0.00577	0.01021	0.00814
	(0.0003)**	(0.0006)**	(0.0005)**
Industry restructuring			
RE	−0.01535	−0.02371	−0.01987
	(0.0043)**	(0.0072)**	(0.0058)**
RE × KNOX	−0.00933	−0.01998	−0.01660
	(0.0040)**	(0.0067)**	(0.0053)**
RE × KTSP	0.00567	0.01442	0.01470
	(0.0051)	(0.0086)*	(0.0069)**
RE × KSO2	0.00798	0.02110	0.01868
	(0.0045)*	(0.0074)**	(0.0059)**

Note(s): Estimated utility dummies are not reported in this table
** (*) denotes significance at the 0.05 (0.10) level

Table 1.

Regarding partial effects among the outputs, the estimated coefficients of the quadratic function between SALR, SALIC, SO_2, CO_2 and NO_X emissions indicate that these good and bad outputs may be substitutes or complements. Table 4 shows that a 10% increase in residential electricity sales is associated with a reduction of 39.7% in industrial-commercial electricity sales for below-average utilities (with both SALR and SALIC below average) and a reduction of 21.5% for above-average utilities (with both SALR and SALIC above average) [3]. These two good outputs are understandably substitutable since electricity generated is sold for either residential or industrial-commercial usage. CO_2 and SO_2 emissions are also interchangeable for two groups of utilities. However, considering utilities having one emission below average and the other above average, CO_2 and SO_2 emissions are complementary for the entire sample [4]. NO_X emissions have a complementary relationship with CO_2 and SO_2 emissions for both groups of utilities and for the whole sample.

We also compute the partial effects of SALR and SALIC on SO_2, CO_2 and NO_X emissions. Larger SALR and SALIC sales typically raise SO_2 and CO_2 emissions, but their impacts on SO_2 emissions vary significantly across two groups. Ten percent increases in SALR and SALIC boost SO_2 emissions from below-average utilities by 16,468 and 5,172 percent, respectively. Meanwhile, SO_2 emissions from above-average utilities rise by 267 and 73%. However, higher SALR and SALIC tend to reduce NO_X emissions.

Now we consider the partial impacts of the inputs on the outputs in Table 5. Holding other things constant, an expansion in capital generally decreases residential but increases industrial–commercial electricity sales slightly. Increases in fuel and labor lead to small reductions in electricity sales. As these power-generating facilities invest 10% more on SO_2 control equipment, their SO_2 emissions decrease only for above-average utilities by 7.4% but

Good outputs	$\partial \overrightarrow{D}_0/\partial y$
SALR	−0.73043
SALIC	−0.33642
Bad outputs	$\partial \overrightarrow{D}_0/\partial \tilde{y}$
SO_2	0.06340
CO_2	0.00230
NO_X	0.00115

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$. These partial derivatives are averages weighted for electricity sales (including residential and industrial-commercial) by utilities

Table 2. Partial derivatives of the directional distance function with respect to outputs

	Below-average utilities	Above-average utilities	All utilities
$\frac{\partial KNOX}{\partial RE}$	−19.97	50.74	5.01
$\frac{\partial KSO2}{\partial RE}$	25.14	5.33	18.49
$\frac{\partial KTSP}{\partial RE}$	2.66	−0.87	1.26
$\frac{\partial SALR}{\partial RE}$	−0.20	0.02	−0.06
$\frac{\partial SALIC}{\partial RE}$	−0.93	−0.84	−0.87

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$

Table 3. Partial effects of restructuring (percent)

	Below-average utilities	Above-average utilities	All utilities
Good outputs			
$\frac{\partial SALIC}{\partial SALR}$	−3.97	−2.15	−2.83
Bad outputs			
$\frac{\partial CO_2}{\partial SO_2}$	−0.01	−0.01	0.01
$\frac{\partial NO_X}{\partial CO_2}$	7.36	7.59	7.29
$\frac{\partial NO_X}{\partial SO_2}$	0.13	0.39	0.32
Bad vs good outputs			
$\frac{\partial SO_2}{\partial SALR}$	1646.83	26.69	439.74
$\frac{\partial SO_2}{\partial SALIC}$	517.20	7.30	121.47
$\frac{\partial CO_2}{\partial SALR}$	4.34	2.53	3.11
$\frac{\partial CO_2}{\partial SALIC}$	1.32	0.70	0.80
$\frac{\partial NO_X}{\partial SALR}$	−34.74	−17.02	−25.32
$\frac{\partial NO_X}{\partial SALIC}$	−15.57	−2.53	−6.56

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$

Table 4. Partial effects among outputs

strikingly increase for below-average utilities by 347.2%. Hence, for the whole sample, SO_2 emissions rise by 85%. The same holds for NO_X control equipment, although its partial effects on NO_X emissions on both groups are reversed. However, larger KTSP installations cut down SO_2 emissions greatly, especially for below-average utilities. In addition, increases in KTSP and KNOX help curb CO_2 emissions marginally.

Table 6 provides estimated technical efficiencies for the direction vector (1, −1) for the good and bad outputs. Technical efficiencies are computed using (18). The weighted-average TE of the 78 utilities in 1988 is 0.87. This measure implies that if the average utility that year were to combine its inputs as effectively as the best-practice utility, then its electricity sales (SO_2, CO_2 and NO_X emissions) would increase (decrease) by about 15% (1/0.87 = 1.15). Between 1988 and 1995, average TE rose from 0.87 to 0.98 but at a decreasing rate. However, after Phase I of the Acid Rain Program came into effect in 1995, the average TE started to decline at an increasing rate from 0.96 in 1996 to 0.93 in 2000. The downward trend reversed in 2001 and then continued its momentum afterward. The short improvement in TE in 2001 is probably attributed to previous adjustments by these utilities to comply with earlier requirements to reduce emissions. By then, several utilities had even stopped their electricity generation. However, this improvement was quickly undermined by stricter environmental regulations.

Table 7 displays average PC, TC and EC, which are calculated using expressions (21), (20) and (19). Technical change, which measures the shift in the production frontier, exhibits a pattern of change similar to that of TE. The frontier first shifted outward at a decreasing rate, but began shifting inward in 1994, earlier than the trending decrease in TE. The inward shift was also interrupted in only 2001. The resulting PC, which is the sum of TC and EC, closely resembles them. The average utility tended to experience declining productivity over time.

	Below-average utilities	Above-average utilities	All utilities
Good outputs			
$\frac{\partial SALR}{\partial CAPITAL}$	0.02	−0.18	−0.08
$\frac{\partial SALIC}{\partial CAPITAL}$	0.07	0.07	0.05
$\frac{\partial SALR}{\partial FUEL}$	−0.15	−0.93	−0.47
$\frac{\partial SALIC}{\partial FUEL}$	−0.64	0.36	−0.004
$\frac{\partial SALR}{\partial LABOR}$	−0.03	−0.27	−0.15
$\frac{\partial SALIC}{\partial LABOR}$	−0.17	0.004	−0.06
Bad outputs			
$\frac{\partial SO_2}{\partial KSO2}$	34.72	−0.74	8.50
$\frac{\partial SO_2}{\partial KNOX}$	14.45	−1.09	5.37
$\frac{\partial SO_2}{\partial KTSP}$	−96.10	−1.63	−40.60
$\frac{\partial NO_X}{\partial KSO2}$	1.48	−1.83	−0.25
$\frac{\partial NO_X}{\partial KNOX}$	−0.81	2.40	0.20
$\frac{\partial NO_X}{\partial KTSP}$	3.84	−1.39	2.73
$\frac{\partial CO_2}{\partial KSO2}$	−0.01	0.42	0.06
$\frac{\partial CO_2}{\partial KNOX}$	0.09	−0.30	−0.04
$\frac{\partial CO_2}{\partial KTSP}$	−0.28	−0.39	−0.27

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$

Table 5.
Partial effects of inputs on outputs

Year	Technical efficiency score Mean	SD
1988	0.87291	0.00154
1989	0.89189	0.00115
1990	0.91125	0.00082
1991	0.93141	0.00054
1992	0.95186	0.00032
1993	0.96438	0.00016
1994	0.97450	0.00008
1995	0.97693	0.00008
1996	0.96444	0.00014
1997	0.95219	0.00028
1998	0.94113	0.00042
1999	0.93083	0.00059
2000	0.93066	0.00065
2001	0.95439	0.00047
2002	0.94087	0.00056
2003	0.93089	0.00076
2004	0.92090	0.00099
2005	0.91107	0.00122

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$

Table 6.
Average utility technical efficiencies

Year	PC	TC	EC
1989	0.03343	0.01344	0.01914
1990	0.03404	0.01307	0.01965
1991	0.03424	0.01264	0.02012
1992	0.00920	0.01223	0.02065
1993	0.00960	0.00335	0.01254
1994	0.00955	−0.00009	0.01013
1995	−0.00123	−0.00833	0.00244
1996	−0.03353	−0.02412	−0.01249
1997	−0.03437	−0.02459	−0.01226
1998	−0.03751	−0.02495	−0.01186
1999	−0.03662	−0.02526	−0.01144
2000	−0.03703	−0.01332	0.00012
2001	0.07122	0.00984	0.02291
2002	−0.02867	−0.02446	−0.01020
2003	−0.02870	−0.02502	−0.01006
2004	−0.02835	−0.02531	−0.00994
2005	−0.02833	−0.02567	−0.00982

Note(s): Direction: $g_y = 1, -g_{\tilde{y}} = -1$

Table 7. Average utility PC, TC and EC

4. Conclusions

This paper estimates a multiple-input, multiple-output directional distance function for electric utilities. Estimation is carried out using a panel of 78 utilities with three alternative sets of direction vectors. During this period, the electric power industry underwent remarkable changes in environmental regulations and a wave of restructuring. The utilities in the sample utilize six inputs (i.e. fuel, labor, capital for generation and capital investments for SO_2, NO_X and particulate removal devices) to produce two good outputs (i.e. residential and industrial-commercial electricity sales) and three bad outputs (i.e. SO_2, CO_2 and NO_X emissions).

Increases in annualized capital costs on SO_2 and NO_X control equipment do not reduce SO_2 and NO_X emissions, respectively. However, expansions of KTSP cut down SO_2 emissions remarkably, and increases in KTSP and KNOX help curb CO_2 emissions marginally. While residential and industrial-commercial electricity sales are substitutable, SO_2, CO_2 and NO_X emissions are generally complementary. In addition, more extensive electricity sales are likely to increase SO_2 and CO_2 emissions but decrease NO_X emissions.

This research finds that restructuring has improved the utilities' performance. Below-average utilities in deregulated markets tend to invest less in NO_X and more in particulate control equipment, but their above-average counterparts do the opposite. However, deregulated utilities generally have more investments for these two as well as SO_2 control systems. Moreover, they reduce their electricity sales slightly. We also find that the utilities' production technologies have moved farther from the frontier over time. This is confirmed by the fact that the average TE started to decline at an increasing rate in 1996. Moreover, the frontier itself has shifted inward since 1993 (except for 2001). This declining productivity is probably attributed to more stringent environmental regulations. These regulations pose a trade-off between electricity output/technical efficiency and emissions. Though, not all utilities invest more in control equipment. The US government should devise other schemes to boost higher investment in emission reduction. They may need to be evaluated by further research.

Notes

1. Refer to Chambers *et al.* (1996) for a theoretical derivation of this function.
2. Hereinafter, all partial effects are calculated in this way.

3. Utilities with one quantity above average and one quantity below average are excluded in the following comparisons.
4. Utilities that do not belong to either below- or above-average group can make partial effects for the whole sample not lie between partial effects for the two groups and even have opposite signs.

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