Production Inefficiency of the U.S. Electricity Industry in the Face of Restructuring and Emission Reduction*

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Abstract

This paper estimates a multiple-input, multiple-output directional distance function for 78 electric utilities spanning from 1988 to 2005. During this period, the electric power industry underwent remarkable changes in environmental regulations and a wave of restructuring. The function allows us to avoid separability, which may eliminate statistically significant interactions among various outputs and to compute the partial effects between or among any pair of endogenous variables. We find that restructuring in electricity markets tends to improve technical efficiency of deregulated utilities. Deregulated utilities that have NO_X control equipment below average are likely to invest less on these devices, but utilities with above average NO_X control equipment do the opposite. The reverse applies to particulate removal devices. However, the whole sample spends more on these two as well as SO_2 control systems and reduce their electricity sales slightly. In addition, increased capital investments in SO_2 and NO_X control equipment do not reduce SO_2 and NO_X emissions, respectively. But expansions of particulate control systems cut down SO_2 emissions greatly. Moreover, the utilities have been shifted increasingly farther from the frontier over time. Inward shifting of the production frontier, as well as declining technical efficiency and productivity growth, probably results from the implementation of stricter environmental regulations.

Keywords: Technical Inefficiency, Technical Change, Productivity Change, Distance Function

1 Introduction

Emissions of sulfur dioxide (SO_2) and nitrogen oxides (NO_X) from electric generating units (EGUs) and other large 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, 2009). Serious 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. 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 how they comply with emission limits.

It has long been recognized that this approach could coordinate pollution abatement activities highly effectively. However, Fowlie (2010) indicates that pre-existing distortions in output markets may hinder the CAT programs from operating efficiently. Restructuring in electricity markets could induce deregulated plants to choose less capital-intensive control technology as compared to regulated or publicly-owned plants. Since regulated utilities enjoy a guaranteed rate of return on capital investment, they tend to relatively over-capitalize their control devices. Fowlie assumes 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 probably 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 U.S. electric utilities in light of multiple inputs and multiple outputs.

To measure the productivity of U.S. electric utilities, Atkinson et al. (2003) use a stochastic distance function that takes into account three inputs (i.e., fuel, labor, and capital), and two good outputs (i.e., residential and industrial-commercial electricity). Then, Atkinson and Dorfman (2005) include one bad output, SO_2 emissions, as a technology shifter. Their results show negative efficiency change over the entire sample period that is largely attributed to firms' efforts to reduce SO_2 emissions. Fu (2009) estimates a directional distance function with a data set comprised of 78 privately-owned electric utilities from 1988 to 2005 with three bad outputs, namely, SO_2, CO_2, and NO_X emissions. She also finds declining efficiency and productivity change over time.

In this paper, we extend Fu's data set 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 eliminate 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 of deregulated utilities since they operate under the discipline of competitive markets. The absence of rate-of-return regulation is likely to 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 reduce their electricity sales slightly.

There are several important interactions among inputs and outputs. Increased capital investments on 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 CO2 emissions marginally. While residential and industrial-commercial electricity sales are substitutable, and 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 technical efficiency and productivity growth, appears to follow the implementation of stricter environmental regulations.

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[1] Refer to Chambers et al. (1996) for a theoretical derivation of this function.

The remainder of the paper is organized as follows. The next section gives a brief overview of the U.S. electric power industry. Section 3 presents properties of the directional distance function and computation of productivity change. Section 4 reports empirical results and conclusions follow in section 5.

2 The U.S. Electric Power Industry

Net generation of electric power in the United States grew steadily over the last two decades from 3,197 million megawatt hours (MWh) in 1993 to 4,157 million MWh in 2007 (Table 1). The average growth rate in this period was 1.89 percent per year. However, the trend reversed in 2001 when California experienced severe electricity shortages and Houston-based Enron got into trouble for fraudulent accounting practices. Electricity generation again dropped 0.9 percent in 2008. The U.S. Energy Information Administration (EIA) attributed the decrease to the weakening economy, with total industrial production falling 2.2 percent, and reduced summer electricity demand for cooling because 2008 produced the coolest temperature in more than a decade.

The primary energy source for generating electric power over this period was coal, which provided about half of total net generation. However, its share of total net generation trended downward, accounting for 48.2 percent in 2008 as compared to 52.9 percent in 1993. The same holds for petroleum and conventional hydroelectric generation. In contrast, natural gas-fired generation sustained solid growth and in 2006 surpassed nuclear generation, whose relative share rose marginally in this period, to become the second largest contributor to total net generation. Renewable energy sources' share of electricity generation (not including conventional hydroelectric) first fell between 1993 and 2001 and then increased consecutively in the last five years, contributing 3.1 percent in 2008. This growth came mainly from wind generation, which was up almost fivefold, from 11.2 million MWh in 2003 to 55.4 million MWh in 2008.

U.S. electric power generation has been shifting gradually from coal and petroleum to natural gas and renewable sources. The change towards 'greener' sources follows significant requirements to reduce SO_2 and NO_X emissions from large stationary sources, primarily EGUs. These emissions contribute to the formation of ozone. High concentration of ozone at ground level can severely exacerbate respiratory diseases and raise the level of susceptibility to respiratory infections, leading to increased medication use, hospital visits and premature mortality. High levels of ozone can also damage sensitive vegetation, causing loss of biodiversity that may reduce the value of real property (US EPA, 2009). Serious health and ecological impacts of air pollution have led to remarkable changes in environmental regulations, beginning with Congress's enacting the Clean Air Act Amendments of 1990.

The Act set a goal of reducing annual SO_2 emissions by 10 million tons below 1980 levels of about 18.9 million tons. The Acid Rain Program (ARP) was established to implement a two-phase tightening of the restrictions. In Phase I of the ARP starting in 1995, 263 units at 110 mostly coal-burning power plants located in 21 eastern and midwestern states were required to cut SO_2 emission rates to 2.5 lbs/million British thermal units (mmBtu). In Phase II, starting in 2000, all fossil-fired units over 75 megawatts had to limit SO_2 emissions to 1.2 lbs/mmBtu. The Act also called for reductions of NO_X emissions by 2 million tons from 1980 levels. The ARP marked a switch from traditional command and control regulatory methods to market-based cap-and-trade systems. It sets a cap on overall emissions (e.g., 8.95 million tons of SO_2 in phase II) and allocates allowances to emit a specified number of tons of emissions. Since allowances are tradable, each utility is flexible in observing emission limits by adopting the cheapest compliance strategy. Therefore, the electricity industry as a whole can reduce emissions cost-effectively.

In 1997, a new, stricter 8-hour ozone standard of 0.08 parts per million was set to replace the 1979 standard, which was 0.12 parts per million. The U.S. Environmental Protection Agency (EPA) developed the NO_X State Implementation Plan (SIP) Call rule in 1998 to reduce ozone season NO_X emissions. The rule was designed to address the problem of ozone transport across the eastern United States (US EPA, 2009). By 2007, all 20 of the affected states and the District of Columbia decided to meet NO_X SIP Call reductions and to join the NO_X Budget Trading Program. This market-based CAT program was displaced by the Clean Air Interstate Rule NO_X ozone season program starting in 2009.

The stringent requirements on SO_2 and NO_X emissions have resulted in dramatic reductions in these air pollutants (Table 2). While unregulated CO_2 emissions increased by 21.8 percent along with electricity generation between 1993 and 2008, SO_2 emissions fell by 47.7 percent, from 15 to 7.8 million tons. NO_X emissions saw an even bigger decrease of 58.4 percent, from 8 to 3.3 million tons. The largest year-over-year declines in SO_2 and NO_X emissions occurred in 1995 and 1996, respectively, when Phase I of the SO_2 reductions under the ARP took effect one year earlier than that of NO_X. Significant decreases in SO_2 and NO_X emissions also occurred in 2008, mostly due to the installation of flue gas desulfurization units, low-NO_X burners and selective catalytic reduction devices (US EIA, 2010).

In addition, the electric power industry underwent a wave of restructuring beginning in the mid-1990s. Before then, electricity generation in the United States was dominated by vertically integrated investor-owned utilities (IOUs), most of which operated as highly regulated, local monopolies. Since prices were set by state regulators based on a guaranteed rate of return on capital investment, large costs caused by inefficient investments would be passed through to customers. It has long been argued that increased competition brought on by deregulation could improve efficiency and reduce prices. In 1996, states that had relatively high electricity rates began restructuring their electric power industry. Under competitive pressure, IOUs have been merging, and many power plants in some regions have been sold to private companies (US EIA, 2005). By 1998, all fifty states and the District of Columbia held formal hearings to consider restructuring. However, the California electricity crisis of 2000 and 2001 halted this transition.

3 The Directional Distance Function

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

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

where $\mathbf{S}(\mathbf{x}, \mathbf{y})$ 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 $\tilde{\mathbf{y}} = (\tilde{y}_1, ..., \tilde{y}_L)' \in R_+^L$ denote a vector of L bad outputs produced jointly with $\mathbf{y}$. Following Chambers et al. (1998), the output directional distance function is defined as

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

where $P(\mathbf{x})$ is the set of good and bad outputs that can be produced with inputs $\mathbf{x}$ 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:

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

D2. g-Homogeneity of Degree Minus One:

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

D3. Good Output Monotonicity:

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

D4. Bad Output Monotonicity:

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

D5. Concavity:

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

D6. Non-negativity:

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

The translation property says that increasing $\mathbf{y}$ and decreasing $\tilde{\mathbf{y}}$ by α-fold of their respective directions will reduce the directional distance by α. Equation (4) implies that if each direction is scaled by λ, then the directional distance will be scaled by λ^{-1}. The next 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. A normalization after estimation of the directional distance function is needed to make sure that D6 holds.

a. 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 (KSO2, 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:

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

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

$$\varepsilon_{it} = \nu_{it} + \mu_{it}. \qquad (10)$$

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, Atkinson, and Crocker (2010), the fixed-effects 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-effects 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.

b. Measuring TE, EC, TC, and PC. This subsection follows Agee, Atkinson, and Crocker (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

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

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

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

or

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

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

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

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

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

where $\ln \hat{D}_0^{F,t}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) = \ln \hat{D}_0^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) + \tilde{u}_t$ is the log of the fitted frontier shadow distance function in period t. Utility i's technical efficiency 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 $\ln \hat{D}_0^{F,t+1}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})$ and $\ln \hat{D}_0^{F,t}(\mathbf{x}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it})$, holding all inputs and outputs constant:

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

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

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

c. Standardizing Units. As discussed in Agee, Atkinson, and Crocker (2010), the output directional distance function involves inputs and outputs that have 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.

d. Choosing Direction. Also as discussed in Agee, Atkinson, and Crocker (2010), the direction is not a parameter that can be estimated. Instead, we can pre-assign the directions with a broad range of values expressing different assumed value judgments relevant to the tradeoffs between good and bad outputs.

4 Data and Empirical Results

a. Data. The data set used in this paper is an extended version of the panel of utilities originally analyzed by Fu (2009). The primary sources for Fu's data are the U.S. Energy Information Administration's *Electric Power Annuals, Forms EIA-767, EIA-906, EIA-920*, and the Federal Energy Regulatory Commission's *Forms FERC-1, FERC-423.* The sample consists of 78 privately-owned U.S. utilities whose electricity generation is fossil fuel-based. A list of the utilities is provided in Table 3. The panel spans from 1988 to 2005, in which major changes in environmental regulations relevant to omission reductions and the wave of industry restructuring took place. 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) in 10 millions of kilowatt hour sales, and three bad outputs (SO_2, CO_2, and NO_X emissions) measured in tons. The inputs initially are fuel, labor, and capital. The quantity of fuel is the heat content in mmBtu 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 U.S. 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. Table 4 reports the annual averages for the quantities of all inputs and outputs.

b. Empirical Results. We standardize the data and estimate the directional distance function (9). Table 5 presents the function estimates corresponding to three alternative sets of direction vectors, following Agee, Atkinson, and Crocker (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 every one 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 an increase in good outputs twice as much as a decrease in bad outputs. We focus on the output direction vector $(g_y, -g_{\tilde{y}}) = (1, -1)$ shown in column three of Table 5 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 6. 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, in markets where electricity prices are no longer set by state regulators but determined by competitive markets instead, deregulated utilities are closer to the frontier. The discipline of competitive markets improves their performance, as expected. However, the partial effect of restructuring on KNOX is different from Fowlie's findings (see Table 7). While below-average utilities (with KNOX below average) in deregulated markets tend to invest 20 percent less on NO_X control equipment, above-average utilities (with KNOX above average) tend to invest 50.7 percent more. The story for KTSP is the opposite. Restructuring induces below-average utilities to spend 2.66 percent more and above-average utilities to spend marginally 0.87 percent 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

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[2] Hereinafter, all partial effects are calculated in this way.

a result of restructuring, these utilities reduce their residential and industrial-commercial electricity sales by 0.06 and 0.87 percent, 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.

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 8 shows that a 10 percent increase in residential electricity sales is associated with a reduction of 39.7 percent in industrial-commercial electricity sales for below-average utilities (with both SALR and SALIC below average) and a reduction of 21.5 percent 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 substitutable for two groups of utilities. However, taking into account utilities having one emission below average and the other emission above average, CO_2 and SO_2 emissions are complementary for the whole 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 greatly across two groups. Ten percent increases in SALR and SALIC boost SO_2 emissions from below-average utilities by 16468 and 5172 percent, re-

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[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.

spectively. Meanwhile, SO_2 emissions from above-average utilities rise by 267 and 73 percent. 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 9. 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 percent more on SO_2 control equipment, their SO_2 emissions decrease only for above-average utilities by 7.4 percent but strikingly increase for below-average utilities by 347.2 percent. Hence, for the whole sample, SO_2 emissions rise by 85 percent. 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 10 provides estimated technical efficiencies for the direction vector $(1, -1)$ for the good and bad outputs. Technical efficiencies are computed using equation (18). The weighted-average technical efficiency 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 percent ($1/0.87 = 1.15$). Between 1988 and 1995, average technical efficiency 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 technical efficiency 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 afterwards. The short improvement in technical efficiency 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 11 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 technical efficiency. The frontier first shifted outward at a decreasing rate, but began shifting inward in 1994, earlier than the trend decrease in technical efficiency. 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.

5 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 spanning from 1988 to 2005 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 spent 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, larger 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 on NO_X and more on 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 technical efficiency 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.

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Table 1: Net Generation (million megawatt hours)

Energy Source	1993	1994	1995	1996	1997	1998	1999	2000
Coal^{a}	1690.1	1690.7	1709.4	1795.2	1845.0	1873.5	1881.1	1966.3
Petroleum^{b}	112.8	105.9	74.6	81.4	92.6	128.8	118.1	111.2
Natural Gas^{c}	414.9	460.2	496.1	455.1	479.4	531.3	556.4	601.0
Nuclear	610.3	640.4	673.4	674.7	628.6	673.7	728.3	753.9
Hydroelectric Conventional^{d}	280.5	260.1	310.8	347.2	356.5	323.3	319.5	275.6
Other Renewables^{e}	76.2	76.5	74.0	75.8	77.2	77.1	79.4	80.9
Wind					3.3	3.0	4.5	5.6
All Energy Sources	3197.2	3247.5	3353.5	3444.2	3492.2	3620.3	3694.8	3802.1
Energy Source	2001	2002	2003	2004	2005	2006	2007	2008
Coal^{a}	1904.0	1933.1	1973.7	1978.3	2012.9	1990.5	2016.5	1985.8
Petroleum^{b}	124.9	94.6	119.4	121.1	122.2	64.2	65.7	46.2
Natural Gas^{c}	639.1	691.0	649.9	710.1	761.0	816.4	896.6	883.0
Nuclear	768.8	780.1	763.7	788.5	782.0	787.2	806.4	806.2
Hydroelectric Conventional^{d}	217.0	264.3	275.8	268.4	270.3	289.2	247.5	254.8
Other Renewables^{e}	70.8	79.1	79.5	83.1	87.3	96.5	105.2	126.2
Wind	6.7	10.4	11.2	14.1	17.8	26.6	34.5	55.4
All Energy Sources	3736.6	3858.5	3883.2	3970.6	4055.4	4064.7	4156.7	4119.4

Notes: [a] Includes anthracite, bituminous, sub-bituminous, and lignite coal.

[b] Includes distillate fuel oil, residual fuel oil, jet fuel, kerosene, petroleum coke, and waste oil.

[c] Includes a small number of generating units for which waste heat is the main energy source.

[d] Excludes pumped storage facilities.

[e] Includes wind, solar thermal and photovoltaic, wood and wood derived fuels, geothermal, and other biomass.

Source: US EIA (2010).

Table 2: Emissions (million metric tons)

	1993	1994	1995	1996	1997	1998	1999	2000
CO_2	2034.2	2063.8	2079.8	2155.5	2253.8	2346.0	2360.4	2464.6
SO_2	15.0	14.5	11.9	12.9	13.5	13.5	12.8	12.0
NO_X	8.0	7.8	7.9	6.3	6.5	6.5	6.0	5.6

	2001	2002	2003	2004	2005	2006	2007	2008
CO_2	2412.0	2417.3	2438.3	2480.0	2536.7	2481.8	2539.8	2477.2
SO_2	11.2	10.9	10.6	10.3	10.3	9.5	9.0	7.8[a]
NO_X	5.3	5.2	4.5	4.1	4.0	3.8	3.7	3.3[a]

Note: [a] SO_2 and NO_X 2008 values are preliminary.

Source: US EIA (2010).

Table 3: Utilities in the Sample

No.	Utility	No.	Utility
1	Alabama Power Co.	40	KGE, A Western Resources Company
2	Central Illinois Public Service Co.	41	Long Island Lighting Co.
3	Union Electric Co.	42	Louisville Gas and Electric Co.
4	Appalachian Power Co.	43	Minnesota Power and Light Co.
5	Arizona Public Service Co.	44	Mississippi Power Co.
6	Atlantic City Electric Co.	45	Montana Dakota Utilities Co.
7	Baltimore Gas and Electric Co.	46	Montana Power Co.
8	Boston Edison Co.	47	New England Power Co.
9	Carolina Power and Light Co.	48	New York State Electric and Gas Corp.
10	Central Hudson Gas and Electric Corp.	49	Niagara Mohawk Power Corp.
11	Central Maine Power Co.	50	Northern Indiana Public Service Co.
12	Central Power and Light Co.	51	Northern States Power Co.
13	Cincinnati Gas and Electric Co.	52	Ohio Edison Co.
14	Central Louisiana Electric Co. Inc.	53	Ohio Power Co.
15	Cleveland Electric Illuminating Co.	54	Oklahoma Gas and Electric Co.
16	Columbus Southern Power Co.	55	Pacific Gas and Electric Co.
17	Commonwealth Edison Co.	56	PacifiCorp West and East
18	Consolidated Edison Co. of NY	57	PECO Energy Co.
19	Dayton Power and Light Co.	58	Pennsylvania Power and Light Co.
20	Delmarva Power and Light Co.	59	Potomac Edison Co.
21	Detroit Edison Co.	60	Potomac Electric Power Co.
22	Duke Power Co.	61	PSC of Colorado
23	Duquesne Light Co.	62	PSC of New Hampshire
24	Entergy Arkansas, Inc.	63	PSC of New Mexico
25	Entergy Gulf States, Inc.	64	PSI Energy, Inc.
26	Entergy Louisiana, Inc.	65	Public Service Electric and Gas Co.
27	Entergy Mississippi, Inc.	66	Rochester Gas and Electric Corp.
28	Entergy New Orleans, Inc.	67	San Diego Gas and Electric Co.
29	Florida Power and Light Co.	68	South Carolina Electric and Gas Co.
30	Florida Power Corp.	69	Southern California Edison Co.
31	Georgia Power Co.	70	Southwestern Electric Power Co.
32	Gulf Power Co.	71	Southwestern Public Service Co.
33	Houston Lighting and Power Co.	72	Tampa Electric Co.
34	Illinois Power Co.	73	Texas Utilities Electric Co.
35	Indiana Michigan Power Co.	74	United Illuminating Co.
36	Indianapolis Power and Light Co.	75	Virginia Electric and Power Co.
37	Interstate Power Co.	76	West Penn Power Co.
38	Kansas City Power and Light Co.	77	Wisconsin Electric Power Co.
39	Kentucky Utilities Co.	78	Wisconsin Public Service Corp.

Table 4: Annual Average Quantities of Inputs and Outputs

Year	X_{FUEL}	X_{LABOR}	X_{CAPITAL}	X_{KSO2}	X_{KNOX}	X_{KTSP}
1988	1.838e+08	1438.5	93944.5	577.2	177.0	306.8
1989	1.869e+08	1477.8	107547.1	598.9	183.6	318.3
1990	1.834e+08	1437.1	106106.6	613.0	189.0	320.2
1991	1.816e+08	1389.7	117412.2	637.9	201.8	327.1
1992	1.821e+08	1333.3	124243.1	647.1	201.2	324.2
1993	1.864e+08	1290.2	137101.1	648.9	205.1	325.2
1994	1.925e+08	1202.6	123890.3	684.7	217.6	333.2
1995	1.920e+08	1101.6	132710.1	741.9	292.0	345.5
1996	1.973e+08	1045.1	134429.2	773.9	355.2	346.0
1997	2.051e+08	1075.2	138174.4	783.6	393.3	350.4
1998	2.145e+08	990.1	151183.8	799.9	406.7	357.3
1999	2.202e+08	1086.7	119609.4	897.1	431.8	357.9
2000	2.260e+08	919.3	121483.3	1030.0	680.0	363.9
2001	2.182e+08	938.8	126314.8	1194.2	801.9	404.2
2002	2.127e+08	1049.7	132421.9	1151.2	869.4	429.5
2003	2.063e+08	1038.5	144887.8	1169.8	909.1	436.3
2004	2.134e+08	972.1	152384.1	1292.4	1024.8	482.0
2005	2.228e+08	968.0	154425.1	1362.1	1101.8	508.0

Year	Y_{SALR}	Y_{SALIC}	$\tilde{Y}_{\text{SO}_2}$	$\tilde{Y}_{\text{CO}_2}$	$\tilde{Y}_{\text{NO}_\text{X}}$
1988	671.6	1320.3	133690.7	15917121	57665.0
1989	685.2	1371.7	141195.2	16600847	60173.0
1990	697.0	1400.0	137864.9	16147149	57361.6
1991	723.7	1412.2	135269.8	16005175	56489.8
1992	705.8	1429.8	131928.5	15899603	54820.4
1993	751.5	1468.0	129788.6	16372633	55903.1
1994	757.6	1512.9	122010.2	16390949	53374.0
1995	789.2	1547.0	99771.3	16259466	52353.9
1996	808.5	1578.0	106228.7	17042418	55511.4
1997	803.5	1612.3	109588.5	17694204	57010.7
1998	845.4	1650.3	101956.3	20365926	57531.8
1999	903.0	1762.3	97846.8	21035890	58636.0
2000	935.2	1785.1	93913.2	21868134	59789.8
2001	963.9	1802.5	91808.4	21020438	36360.8
2002	973.1	1727.0	89818.1	20656698	36836.7
2003	981.1	1717.5	88446.3	20369512	35975.3
2004	996.1	1776.8	91267.0	20956468	38734.1
2005	1041.6	1798.8	96342.2	21821084	54388.3

Notes: X_{FUEL} is the heat content in mmBtu. X_{CAPITAL} is the expenditure on capital (in \$10,000) divided by the yield of the utility's latest issue of long-term debt. X_{KSO2}, X_{KNOX}, and X_{KTSP} are in \$10,000. Y_{SALR} and Y_{SALIC} are in 10 millions of kilowatt hour sales. $\tilde{Y}_{\text{SO}_2}$, $\tilde{Y}_{\text{CO}_2}$, and $\tilde{Y}_{\text{NO}_\text{X}}$ are omissions measured in tons.

Table 5: Estimation Results

Variable	Coefficient (standard error)		
	$g_y = 2; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -2$
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)**	(.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 × CO_2	-0.02352	-0.02773	-0.00232
	(0.0077)**	(0.0096)**	(0.0056)
SO_2 × NO_X	-0.00361	-0.00484	-0.00402
	(0.0048)	(0.0080)	(0.0063)
CO_2 × 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)**

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	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)**
(KSO2)^2	-0.00707	-0.01450	-0.01518
	(0.0064)	(0.0108)	(0.0086)*
KNOX^2	0.02496	0.04114	0.02792
	(0.0045)**	(0.0076)**	(0.0060)**
KTSP^2	-0.01195	-0.01731	-0.01179
	(0.0093)	(0.0156)	(0.0124)
FUEL × LABOR	0.01077	0.01459	0.00289
	(0.0055)*	(0.0082)*	(0.0058)
FUEL × CAPITAL	0.03782	0.04417	0.02509
	(0.0063)**	(0.0089)**	(0.0063)**
FUEL × KSO2	0.02933	0.03543	0.01712
	(0.0079)**	(0.0125)**	(0.0090)*
FUEL × KNOX	0.01737	0.02196	0.00102
	(0.0078)**	(0.0112)**	(0.0074)
FUEL × KTSP	0.02974	0.02598	0.00303
	(0.0084)**	(0.0138)*	(0.0106)
LABOR × CAPITAL	0.00024	-0.00641	-0.01090
	(0.0029)	(0.0049)	(0.0039)**
LABOR × KSO2	0.02324	0.03663	0.02089
	(0.0040)**	(0.0066)**	(0.0053)**
LABOR × KNOX	0.00027	0.00236	0.00217
	(0.0020)	(0.0035)	(0.0029)
LABOR × KTSP	0.01078	0.00938	0.00191
	(0.0027)**	(0.0046)**	(0.0037)
CAPITAL × KSO2	0.00838	0.01419	0.01436
	(0.0035)**	(0.0059)**	(0.0047)**

Variable	Coefficient (standard error)		
	$g_y = 2; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -1$	$g_y = 1; -g_{\tilde{y}} = -2$
CAPITAL × KNOX	-0.00671	-0.01021	-0.00505
	(0.0027)**	(0.0046)**	(0.0037)
CAPITAL × KTSP	0.00210	-0.00110	-0.00065
	(0.0036)	(0.0060)	(0.0048)
KNOX × KTSP	0.00844	0.01349	0.00285
	(0.0047)*	(0.0082)*	(0.0067)
KNOX × KSO2	-0.01303	-0.02053	-0.01567
	(0.0023)**	(0.0039)**	(0.0032)**
KTSP × KSO2	-0.00039	0.00470	0.00877
	(0.0045)	(0.0074)	(0.0059)
Interaction terms among Inputs and Outputs:			
FUEL × SALIC	-0.01399	0.00513	0.00193
	(0.0141)	(0.0214)	(0.0154)
FUEL × SO_2	0.03721	0.06938	0.05167
	(0.0098)**	(0.0144)**	(0.0098)**
FUEL × CO_2	-0.16882	-0.24292	-0.12721
	(0.0157)**	(0.0207)**	(0.01313)**
FUEL × NO_X	0.01857	0.03780	0.02536
	(0.0129)	(0.0183)**	(0.0123)**
LABOR × SALIC	0.00786	0.01629	0.01560
	(0.0056)	(0.0096)*	(0.0079)*
LABOR × SO_2	-0.00364	-0.01315	-0.01623
	(0.0029)	(0.0049)**	(0.0039)**
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)

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 × 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)**

Notes: Estimated utility dummies are not reported in this table.

** (*) denotes significance at the 0.05 (0.10) level.

Table 6: Partial Derivatives of the Directional Distance Function with Respect to Outputs
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

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: These partial derivatives are averages weighted for electricity sales (including residential and industrial-commercial) by utilities.

Table 7: Partial Effects of Restructuring (percent)
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

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

Table 8: Partial Effects Among Outputs
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

	Below-average utilities	Above-average utilities	All utilities
Good Outputs			
$\frac{\partial \text{SALIC}}{\partial \text{SALR}}$	-3.97	-2.15	-2.83
Bad Outputs			
$\frac{\partial \text{CO}_2}{\partial \text{SO}_2}$	-0.01	-0.01	0.01
$\frac{\partial \text{NO}_\text{X}}{\partial \text{CO}_2}$	7.36	7.59	7.29
$\frac{\partial \text{NO}_\text{X}}{\partial \text{SO}_2}$	0.13	0.39	0.32
Bad vs. Good Outputs			
$\frac{\partial \text{SO}_2}{\partial \text{SALR}}$	1646.83	26.69	439.74
$\frac{\partial \text{SO}_2}{\partial \text{SALIC}}$	517.20	7.30	121.47
$\frac{\partial \text{CO}_2}{\partial \text{SALR}}$	4.34	2.53	3.11
$\frac{\partial \text{CO}_2}{\partial \text{SALIC}}$	1.32	0.70	0.80
$\frac{\partial \text{NO}_\text{X}}{\partial \text{SALR}}$	-34.74	-17.02	-25.32
$\frac{\partial \text{NO}_\text{X}}{\partial \text{SALIC}}$	-15.57	-2.53	-6.56

Table 9: Partial Effects of Inputs on Outputs
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

	Below-average utilities	Above-average utilities	All utilities
Good Outputs			
$\frac{\partial \text{SALR}}{\partial \text{CAPITAL}}$	0.02	-0.18	-0.08
$\frac{\partial \text{SALIC}}{\partial \text{CAPITAL}}$	0.07	0.07	0.05
$\frac{\partial \text{SALR}}{\partial \text{FUEL}}$	-0.15	-0.93	-0.47
$\frac{\partial \text{SALIC}}{\partial \text{FUEL}}$	-0.64	0.36	-0.004
$\frac{\partial \text{SALR}}{\partial \text{LABOR}}$	-0.03	-0.27	-0.15
$\frac{\partial \text{SALIC}}{\partial \text{LABOR}}$	-0.17	0.004	-0.06
Bad Outputs			
$\frac{\partial \text{SO}_2}{\partial \text{KSO2}}$	34.72	-0.74	8.50
$\frac{\partial \text{SO}_2}{\partial \text{KNOX}}$	14.45	-1.09	5.37
$\frac{\partial \text{SO}_2}{\partial \text{KTSP}}$	-96.10	-1.63	-40.60
$\frac{\partial \text{NO}_\text{X}}{\partial \text{KSO2}}$	1.48	-1.83	-0.25
$\frac{\partial \text{NO}_\text{X}}{\partial \text{KNOX}}$	-0.81	2.40	0.20
$\frac{\partial \text{NO}_\text{X}}{\partial \text{KTSP}}$	3.84	-1.39	2.73
$\frac{\partial \text{CO}_2}{\partial \text{KSO2}}$	-0.01	0.42	0.06
$\frac{\partial \text{CO}_2}{\partial \text{KNOX}}$	0.09	-0.30	-0.04
$\frac{\partial \text{CO}_2}{\partial \text{KTSP}}$	-0.28	-0.39	-0.27

Table 10: Average Utility Technical Efficiencies
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

	Technical Efficiency Score	
Year	Mean	Std. Dev.
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

Table 11: Average Utility PC, TC, and EC
(Direction: $g_y = 1, -g_{\tilde{y}} = -1$)

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