ESSAYS ON PRODUCTIVITY AND EFFICIENCY ANALYSIS IN THE U.S. ELECTRIC UTILITY INDUSTRY

by

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(Under the direction of Scott E. Atkinson)

ABSTRACT

In the past decade, as the environmental effects of emissions have become better understood, electric utility firms in the United States have faced increasing regulation. Meanwhile, with technology advances and increasing regional price disparity, a wave of deregulation policies have led to drastic structural changes in some states. Expanding on the previous literature, I conduct two empirical analyses of this industry. First, I estimate productivity and efficiency change and then I use these results to address questions in two subjects: the effect of environmental regulations and industry structural change.

The first essay studies 78 major privately-owned electric utilities from 1988–2005, when government regulations reduced the allowable levels of pollutants, often dramatically. I estimate three models for the production of multiple inputs and multiple outputs with negative externalities: the traditional input distance function treating emissions as technology shifters, a quadratic output directional distance function with no emissions, and the directional distance function that credits firms for desirable goods and penalizes them for pollutants. I compare two approaches to the measurement of productivity growth and efficiency change: a Malmquist productivity index approach, based on ratios of the estimated distances, and a difference-in-log-distances approach. My results show higher productivity growth from the second approach. Additionally, I introduce a binary variable in the estimation of directional distances to distinguish firms that continuously generated steam electricity throughout my sample period from those that ceased production during this timeframe. My results show that firms that stopped their steam electricity generation were less efficient. Therefore, as environmental regulations reshaped this industry, more efficient and productive firms survived environmental regulatory changes and kept growing.

The second essay is based on a panel data set of 377 fossil-fuel power plants from 1998–2005, when a substantial structural change occurred in response to deregulation policies. I estimate directional distance functions to model production, controlling for the effect of deregulation. I find that plants subject to deregulation tend to decrease their capital expenditure, labor and fuel consumption, but not necessarily lower emissions. Also I apply the Luenberger index approach to compute technical efficiency and productivity change and show that plants in deregulation states have slightly higher PC and EC.

Index words: Productivity, Technical Efficiency, Distance Function, Directional Distance Function, Deregulation

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Dedication

I dedicate my dissertation work to my loving parents and my dearest sister for their support and encouragement over the years.

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1.1 Introduction

Since the late 1990s, a significant structural change in the U.S. utility industry has taken place. Many fossil-fuel power plants have greatly reduced or stopped their steam electricity generation by merging with other firms, selling off or shutting down their steam-generating assets and becoming electricity wholesalers and distributors. Out of the sample of 78 major privately-owned U.S. utilities that I followed between 1988 and 2005, 25 completely stopped steam electricity generation from 1999, mostly in 2000, 2001, and 2002. Six other utilities greatly reduced fuel inputs in production, cutting their fuel expenditure by as much as three-quarters since 1999.

Fossil fuels have been the primary energy source for electricity generation in the U.S. Fossile fuel are comprised of three major types: coal, petroleum, and natural gas. Table (1.1) shows the overall trend of U.S. electricity generation and the share of different energy sources. The total net generation has been growing steadily over the years. The share of electricity output generated from coal consumption is the largest among all energy sources; however, it has been trending downward from around 55% in the early 1990s to only 37.4% in 2012. Meanwhile, the share of electricity generated from natural gas has increased substantially, offsetting the shrinkage in coal consumption. Overall, fossil fuels account for about 70% of the net electricity generation, followed by nuclear energy with around 20% over the past two decades.

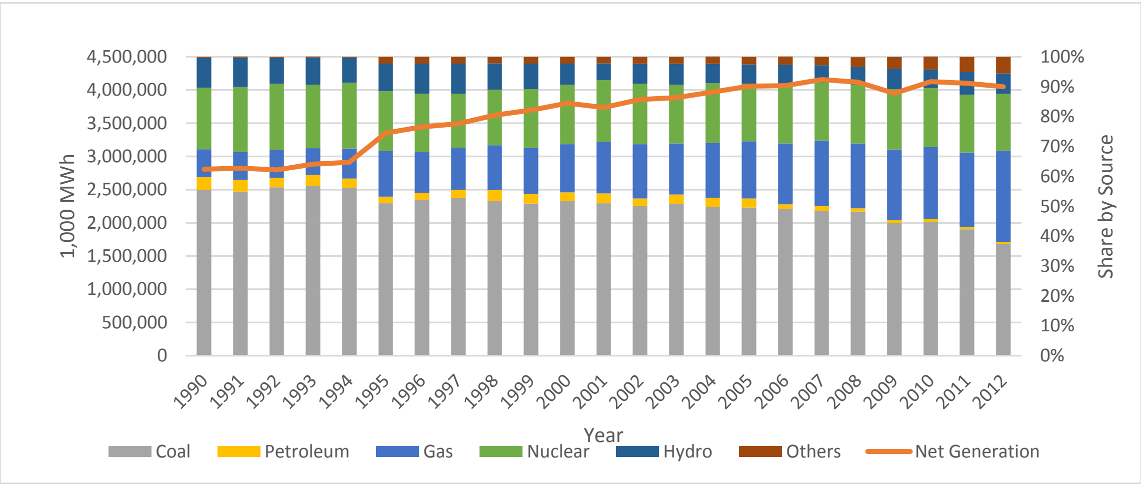
Table 1.1: U.S. Net Electricity Generation by Energy Source, 1996-2012

	Net Generation	Share of Energy Source					
Year	(1,000 MWh)	Coal	Petroleum	Gas	Nuclear	Hydro	Others
1990	2,808,151	55.5%	4.2%	9.4%	20.5%	10.0%	0.4%
1991	2,825,023	54.9%	3.9%	9.4%	21.7%	9.8%	0.4%
1992	2,797,219	56.3%	3.2%	9.4%	22.1%	8.6%	0.4%
1993	2,882,525	56.9%	3.5%	9.0%	21.2%	9.2%	0.3%
1994	2,910,712	56.2%	3.1%	10.0%	22.0%	8.4%	0.3%
1995	3,353,487	51.0%	2.2%	15.2%	20.1%	9.2%	2.3%
1996	3,444,188	52.1%	2.4%	13.6%	19.6%	10.0%	2.3%
1997	3,492,172	52.8%	2.7%	14.1%	18.0%	10.1%	2.3%
1998	3,620,295	51.8%	3.6%	15.0%	18.6%	8.8%	2.2%
1999	3,694,810	50.9%	3.2%	15.4%	19.7%	8.5%	2.3%
2000	3,802,105	51.7%	2.9%	16.2%	19.8%	7.1%	2.3%
2001	3,736,643	51.0%	3.3%	17.3%	20.6%	5.6%	2.2%
2002	3,858,453	50.1%	2.5%	18.2%	20.2%	6.6%	2.4%
2003	3,883,186	50.8%	3.1%	17.1%	19.7%	6.9%	2.4%
2004	3,970,555	49.8%	3.1%	18.3%	19.9%	6.5%	2.5%
2005	4,055,421	49.6%	3.0%	19.1%	19.3%	6.5%	2.5%
2006	4,064,702	49.0%	1.6%	20.4%	19.4%	7.0%	2.7%
2007	4,156,746	48.5%	1.6%	21.9%	19.4%	5.8%	2.8%
2008	4,119,387	48.2%	1.1%	21.7%	19.6%	6.0%	3.3%
2009	3,950,331	44.4%	1.0%	23.6%	20.2%	6.8%	4.0%
2010	4,125,058	44.8%	0.9%	24.2%	19.6%	6.2%	4.4%
2011	4,100,657	42.3%	0.7%	25.0%	19.3%	7.6%	5.1%
2012	4,047,765	37.4%	0.6%	30.6%	19.0%	6.8%	5.6%

Source: EIA (1994, 2006, 2013).

Figure (1.1) summarizes table (1.1). The shift in energy sources reflects technological advances, changing energy prices, and the effects of stringent environmental regulations on utility firms.

Figure 1.1: U.S. Electricity Net Generation and Share of Energy Source



Source: EIA (1994, 2006, 2013).

Fossil-fueled steam-electric-generating firms create negative externalities during their production process which emit carbon dioxide (CO_2), sulfur dioxide (SO_2), nitrogen oxide (NO_X), and ash particulates. These emissions have a negative impact on the environment and human health. CO_2 is the primary greenhouse gas, a source of global warming. Fossil-fuel combustion during the electricity generation process is the largest single source of CO_2 emissions in the U.S., accounting for about 38% of total CO_2 emissions and 32% of total greenhouse gas emissions in 2011 in the nation.[1] Between 1990 and 2012, SO_2 and NO_X emissions were the primary causes of acid rain, which is harmful to the acqutic environment and poses risks to many plants and animals that live in water. This pollutant also damages forests, causing slower growth, injury, or death of forests. Moreover, acid rain is harmful to human health through the increased risks of heart and lung diseases.

[1] EPA 430-R-13-001, "Inventory of U.S. Greenhouse Gas Emissions and Sinks: 1990 - 2011.", April 12, 2013.

Demand for electricity has slowly increased over time (with about 2% annual growth rate in U.S. electricity demand since the 1990s according to the EIA).[2] When air pollution is not regulated, the social cost of electricity generation is greater than the firms' production cost; in equilibrium, firms will then over-produce. In the United States, a major change in the environmental regulation of air pollution began with the passage of Title IV of the 1990 Clean Air Act Amendment, which focuses primarily on SO_2 and NO_X emissions. This is also known as the Acid Rain Program. It is a market-based initiative taken by the United States Environmental Protection Agency (EPA) in an effort to reduce overall atmospheric levels of SO_2 and NO_X. The program implemented a cap-and-trade emissions trading system that primarily targets coal-burning power plants, allowing them to buy and sell emission permits (called "allowances") according to individual needs and costs. The program requires a two-phase tightening of the restrictions placed on fossil-fuel power plants; phase I started in 1995, and phase II began in 2000. The cap-and-trade system for SO_2 emissions was established in 1996 and for NO_X emissions in 1999. Under both programs, there has been substantial reduction in SO_2 and NO_X emissions. However, CO_2 emissions, a major source of greenhouse gases, have yet to be federally regulated in the United States. A regional cap-and-trade system for CO_2 emissions, the Regional Greenhouse Gas Initiative (RGGI), was implemented in 2009 in nine states in the Northeast and Mid-Atlantic regions. In addition, California is currently establishing a cap-and-trade program on greenhouse gas. However, at the federal level, policies on reducing CO_2 emissions are still under debate.

As electric utilities are forced to take into account their emissions and internalize their costs, all else being equal, we would expect to see a decrease in the supply of steam electricity generation. An interesting question that emerges is whether these increasingly stringent environmental regulations—designed to encourage firms to engage in emission abatement and technology innovation—lead the electric utility industry to self-select firms with higher levels of productivity and efficiency and whether existing firms become more efficient. I also

[2] DOE/EIA-0383, "Annual Energy Outlook 2009 with Projections to 2030." http://www.eia.doe.gov/oiaf/aeo/electricity.html, March 2009.

wish to measure the extent to which crediting firms for pollution reduction affects their measured productivity growth.

In the framework of multiple inputs and multiple outputs and in the presence of undesirable outputs, one way to measure productivity is to apply the distance-function model (e.g., Atkinson, Cornwell, and Honerkamp, 2003) and treat the bad outputs as negative inputs or treat them as an exogenous technology shifter (Atkinson and Dorfman, 2005). The advantage of the distance-function approach is that it allows the measurement of productivity change and efficiency change for multiple outputs and multiple inputs. Atkinson and Dorfman (2005) applied the input-distance function to the electric utility industry, included SO_2 as a technology shifter, and found substantial, negative efficiency change and declining productivity change over the sample period from 1980 to 1995. They concluded that these results reflected firms' pollution abatement.

An extension of Shephard's (1953, 1970) distance function is the directional distance function (e.g., Chambers, Chung, and Färe, 1998; Chung, Färe, and Grosskopf 1997). Chambers, Chung, and Färe (1998) provided a thorough theoretical study of the directional distance function, and stated that it is a generalization of existing distance functions that allows one to scale input and output vectors simultaneously in a pre-assigned direction. This approach can be particularly useful for modeling a production process that involves multiple inputs and multiple outputs, some of which may be economic bads. Färe et al. (2005) employed a quadratic directional output distance function to estimate technical efficiency in the U.S. electric utility industry, including SO_2 emissions, for the years 1993 and 1997. They estimated the shadow price of SO_2 and the output elasticity of substitution between electricity and SO_2, and found that Phase I of the Acid Rain Program was effective in reducing SO_2 emissions but that further reductions would be increasingly costly at the margin.

To measure and compare firms' production performances, one can compute key indicators, such as productivity and efficiency measures based on the directional distances. Productivity is defined as the ratio of outputs to inputs, and productivity growth measures the difference between output growth and input growth. Economic efficiency has two components: technical efficiency and allocative efficiency. Technical efficiency refers to the ability to produce as much output as possible for a given technology level and input usage or alternatively, the ability to use as little input as required for a given level of technology and outputs. Allocative efficiency refers to choosing the optimal combination of inputs and outputs, given prevailing prices. The traditional distance function and the directional distance function allow us to measure technical change (TC), which is the shift in the production frontier, efficiency change (EC), which is the movement toward the frontier, and productivity change (PC), which is the sum of EC and TC.

In studies focused on productivity and efficiency, two main approaches prevail: an econometric approach and a mathematical programming one. This chapter uses the econometric approach. Greene (2008) summarized different modeling techniques used in a variety of empirical studies that focused on efficiency analysis. I use and compare two alternative methods in this paper. The first is the index-number approach: TC, EC, and PC can be measured by Malmquist productivity indexes based on the ratio of input or output distances, or by Lunenberger productivity indicators based on directional distance functions. Färe, Grosskopf and Margaritis (2008) surveyed studies of Malmquist productivity indexes and other modified indexes. The second method measures TC, EC and PC by computing the difference in log distances using and estimated distance stochastic frontier model.

To estimate productivity and efficiency change over time, I employ a dataset of 78 privately owned U.S. electric utilities, and track their air pollution emission information collected by the U.S. Department of Energy (EIA) and the Federal Energy Regulatory Commission (FERC) between 1988 and 2005. I examine the effects of three types of emissions — CO_2, SO_2, and NO_X, the major emissions of the fossil-fuel-based steam-electricity generation industry — associated with the change in industry structure that took place in the late 1990s. To examine whether environmental regulations have a positive effect on industry productivity growth, I compare the productivity and efficiency of the firms that chose to sell or shut down their steam-electricity-generating production and those that remained in business. My analysis seeks to answer three questions. First, what is the overall trend in efficiency change and productivity growth in the U.S. fossil-fuel electric utility industry from 1998 to 2005, a period when regulations on air pollution became more stringent? How do my results compare to the existing literature in which no emissions or only one type of emission is modeled? Second, based on the distance-function approach to modeling multiple inputs and multiple outputs with undesirable by-products, what are the differences between the index-number approach and the difference-in-log-distances approach in the estimation of technical efficiency and productivity change? Third, are there any differences in the efficiency and productivity growth of the firms that remained in business after changes in environmental regulations and the firms that shut down or merged with other firms and ceased steam-electricity generation?

I conducted my analysis as follows. First, I use an unbalanced panel data set that includes 78 firms over 18 years to estimate the output-directional distances. For the index-number approach, by which I compute Malmquist productivity index and obtain the percentage change in PC, TC and EC, I follow Chambers, Chung, and Färe (1998) and transform fitted output-directional distances to output distances. Next, I use a difference-in-log-distances approach, as in Agee, Atkinson, and Crocker (2008), and directly estimate firm technical inefficiency from the output directional distances. I then compare the empirical results from both methods. Specifically, I estimate a translog input distance function, treating emissions as technology shifters, and recalculate the efficiency and productivity changes. In addition, I look at the yearly weighted-average change in technical efficiency and productivity to determine whether the declining efficiency and productivity changes found by Atkinson and Dorfman (2005) are also observed during my sample period, especially after the regulation changes. Last, I divide the sample into two groups of firms based on whether or not the firms continued to generate steam electricity throughout the sample period. I introduce a binary variable into the specification of the output directional distance functions, and interact it with the input and output variables to determine whether the two types of firms are different in terms of technical inefficiency.

This study builds on previous research in several ways. First, I study the industry productivity and efficiency to determine whether more stringent environmental regulations induced the industry to self-select firms that are more productive and efficient, and therefore contribute to industry growth. Previous studies analyzing productivity and efficiency have not addressed this subject. Second, in a multiple-inputs, multiple-outputs model in which undesirable by-products exist, I incorporate the environmental effect of three major emissions into the directional distance function — CO_2, SO_2, and NO_X — and thus take into account different phases of pollution control for each. Previous studies often omit all pollutants or focus on only one of these emissions. Third, the data used in this study are collected from EIA, EPA, FERC, and Moody's. Calculating firm-level inputs, outputs, emissions, and financial indicators from raw data was no easy task, as they are no longer reported directly. To my knowledge, no previous studies have conducted analyses based on these data.

1.2 Econometric Models

1.2.1 The Distance Function

Distance functions allow the measurement of productivity and efficiency in a multiple-input and multiple-output framework. Consider a production technology with multiple inputs and outputs. Let $\mathbf{x}$ be a vector of inputs, $\mathbf{x}=(\mathrm{x}_1,...,\mathrm{x}_N) \in \mathrm{R}^N_+$, and let $\mathbf{y}$ be a vector of outputs, $\mathbf{y}=(\mathrm{y}_1,...,\mathrm{y}_M) \in \mathrm{R}^M_+$; then the production technology, $\mathrm{P}(\mathbf{x}, \mathbf{y},\mathrm{t})$, can be described as

$$P(\mathbf{x}, \mathbf{y}, t) = \{(\mathbf{x}, \mathbf{y}) : \ \mathbf{x} \text{ can produce } \mathbf{y} \text{ at time } t\}, \tag{1.1}$$

where t=1,...,T is time. A general form of the input distance function can be defined as

$$D_i(\mathbf{y}, \mathbf{x}, t) = \sup_{\lambda}\{(\lambda : \ (\mathbf{x}/\lambda, \mathbf{y}) \in P(\mathbf{x}, \mathbf{y}, t)\}, \tag{1.2}$$

and the output distance function is defined as

$$D_o(\mathbf{x}, \mathbf{y}, t) = \inf_{\theta}\{(\theta : \ (\mathbf{x}, \mathbf{y}/\theta) \in P(\mathbf{x}, \mathbf{y}, t)\}. \tag{1.3}$$

Therefore, the input distance function describes the production technology where producers minimize input quantities for a given level of outputs at time t, and the value of the input distance function will be greater than or equal to 1 for its feasible set. When the value is equal to 1, the production process is operating on the efficient frontier. Similarly, the output distance function describes the production technology when producers maximize the quantity of outputs for a given level of inputs at time t. The output distance function takes a value of less than or equal to 1, with production occurring on the efficient frontier when it equals 1. However, when there are bad outputs as by-products, applying the classic distance-function approach could cause misspecification errors. This is because neither the input- nor the output-distance function can simultaneously credit firms for expanding their good outputs, reducing their inputs, and reducing their bad outputs. The directional distance function can easily handle bad inputs and outputs because it allows one to assign different directions to expand or contract multiple inputs and outputs, both good and bad.

1.2.2 The Directional Distance Function

In this paper, I apply the directional distance function to U.S. fossil-fuel steam-electricity generation. Production technology is defined as

$$P(\mathbf{x}, \mathbf{y}, \mathbf{b}, t) = \{(\mathbf{x}, \mathbf{y}, \mathbf{b}) : \ \mathbf{x} \text{ can produce } \mathbf{y} \text{ and pollute } \mathbf{b} \text{ at time } t\}. \tag{1.4}$$

In this application, the input vector $\mathbf{x}$ includes capital, labor, and energy; the good output vector $\mathbf{y}$ refers to electricity generation that is sold for residential, industrial, and commercial use, measured in kilowatt hours(kWh); and the bad output vector $\mathbf{b}$=(b$_1$,...b$_B$) $\in \mathrm{R}_+^B$ measures the pollution by-product in tons of CO_2, SO_2, and NO_X emissions. The standard axioms for distance functions also apply in this model:

(a1) P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t) is closed and convex;

(a2) Inputs and good outputs are strongly disposable, i.e., if ($\mathbf{x}$,$\mathbf{y}$) $\in$ P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t) and ($\mathbf{x}\prime$, -$\mathbf{y}\prime$) $\geq$ ($\mathbf{x}$, -$\mathbf{y}$), then ($\mathbf{x}\prime$, -$\mathbf{y}\prime$) $\in$ P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t);

(a3) The good and bad outputs are (together) weakly disposable (Shephard 1970), i.e., if ($\mathbf{y}$, $\mathbf{b}$) $\in$ P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t) and $\theta \in$ [0,1] then ($\theta\mathbf{y}$, $\theta\mathbf{b}$) $\in$ P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t);

(a4) The good and bad outputs are produced jointly, i.e., if ($\mathbf{y}$,$\mathbf{b}$,) $\in$ P($\mathbf{x}$, $\mathbf{y}$,$\mathbf{b}$,t) and $\mathbf{b}$=0 then $\mathbf{y}$=0.

The assumption (a2) implies that, for a given production technology, an increased level of inputs and/or contracted level of good outputs are possible; (a3) implies that reducing pollution is costly; that is, contracting bad outputs is possible if good outputs are also reduced proportionally for a given level of inputs; and (a4) indicates that the good and bad outputs are jointly produced in this technology; if no bad outputs are produced, then it is not possible to produce any amount of good outputs.

The directional output distance function is defined as

$$\overrightarrow{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}, t; g_y, -g_b) = \sup\{(\beta : \ (\mathbf{y} + \beta g_y, \mathbf{b} - \beta g_b) \in P(\mathbf{x}, \mathbf{y}, \mathbf{b}, t)\}, \tag{1.5}$$

where (g_y,g_b)$\neq$(0,0) is a direction vector. The output directional distance function increases good outputs and decreases bad outputs simultaneously in the direction of (g_y,-g_b) for a given level of inputs. It takes a value of 0 if the production is on the efficient frontier and a value greater than 0 if it is inefficient. The directional output distance function has the following properties:

(p1) $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t; g_y, -g_b) $\geq 0 \Leftrightarrow$ ($\mathbf{y}$, $\mathbf{b}$) $\in$ P($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t);

(p2) ($\mathbf{y}\prime$, $\mathbf{b}$) $\leq$ ($\mathbf{y}$, $\mathbf{b}$) $\Rightarrow$ $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}\prime$, $\mathbf{b}$, t; g_y, -g_b) $\geq$ $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t; g_y, -g_b);

(p3) ($\mathbf{y}$, $\mathbf{b}\prime$) $\geq$ ($\mathbf{y}$, $\mathbf{b}$) $\Rightarrow$ $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}\prime$, t; g_y, -g_b) $\geq$ $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t; g_y, -g_b);

(p4) ($\mathbf{y}$, $\mathbf{b}$) $\in$ P($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t) and $\theta \in$ [0,1] $\Rightarrow$ $\overrightarrow{D}_o$($\mathbf{x}$, θ $\mathbf{y}$, θ $\mathbf{b}$, t; g_y, -g_b) $\geq$ 0;

(p5) $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$ + αg_y, $\mathbf{b}$ - αg_b, t; g_y, -g_b) = $\overrightarrow{D}_o$($\mathbf{x}$, $\mathbf{y}$, $\mathbf{b}$, t; g_y, -g_b) - α.

Property (p1) states that the directional output distance function is non-negative for feasible output vectors. Property (p2) requires the strong disposability of the good outputs, which is analogous to axiom (a2). If good outputs decrease, holding inputs and bad outputs constant, inefficiency will not decrease. Property (p3) is another monotonicity property which states that if bad outputs increase, holding inputs and good outputs constant, inefficiency will not decrease. Property (p4) refers to the weak disposability of good and bad outputs jointly, which is analogous to axiom (a3). The last property, (p5), is the translation property, which says that if good outputs are expanded by αg_y and bad outputs are contracted by αg_b, then the value of the directional output distance function will decrease (production will be more efficient) by the amount α.

Since Shephard's (1953, 1970) output distance function is a special case of the directional distance function, there exists an exact relation between the two (Chambers, Chung, and Färe, 1998):

$$\vec{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}) = \frac{1}{D_o(\mathbf{x}, \mathbf{y}, \mathbf{b})} - 1. \tag{1.6}$$

1.2.3 Measurement of Productivity Growth and Efficiency Change

Index Numbers Approach

Distance-function-based measures of productivity include Malmquist productivity indices, Luenberger productivity indicators, and Hicks-Moorsteen productivity indices. Malmquist productivity indices, introduced by Caves et al. (1981), can be computed from traditional distance functions and can be either input- or output-oriented, as a ratio of the distances. A Malmquist productivity index based on the output distance functions at time t is defined as

$$M_o^t = \frac{D_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_o^t(\mathbf{x}^t, \mathbf{y}^t)}. \tag{1.7}$$

To measure productivity change using Malmquist indices, M_o, I apply

$$\begin{aligned} PC &= (M_o^t \cdot M_o^{t+1})^{1/2} \\ &= (\frac{D_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_o^t(\mathbf{x}^t, \mathbf{y}^t)} \frac{D_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t)})^{1/2}. \end{aligned} \tag{1.8}$$

The Malmquist productivity index can be decomposed into efficiency change and technical change; that is,

$$M_o = EC \cdot TC, \tag{1.9}$$

where

$$EC = D_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}) / D_o^t(\mathbf{x}^t, \mathbf{y}^t), \tag{1.10}$$

and

$$TC = \left(\frac{D_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})}{D_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1})} \frac{D_o^t(\mathbf{x}^t, \mathbf{y}^t)}{D_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t)}\right)^{1/2}. \tag{1.11}$$

In contrast, the Luenberger productivity indicator, introduced by Chambers (1996), is constructed from the directional distance functions. Instead of ratios of distance functions, the Luenberger index uses the differences of the distance functions, giving it an additive structure. As the directional distance functions allow the simultaneous expansion of good outputs and decrease of undesirable outputs, the Luenberger measures of productivity and efficiency can capture this simultaneous effect. The Luenberger indicator is defined as:

$$\begin{aligned} L = \frac{1}{2}(L^{t+1} + L^t) \quad &= \quad \frac{1}{2}[\overrightarrow{D}_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) - \overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}) \\ &\quad + \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) - \overrightarrow{D}_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})]. \end{aligned} \tag{1.12}$$

It can also be decomposed into efficiency change (LEC) and technical change (LTC):

$$LEC = \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) - \overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}), \tag{1.13}$$

and

$$\begin{aligned} LTC \quad &= \quad \frac{1}{2}[\overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}) - \overrightarrow{D}_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1}) \\ &\quad + \overrightarrow{D}_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t) - \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)]. \end{aligned} \tag{1.14}$$

To measure PC, TC, and EC in terms of percentage changes, the output directional distance function-based indicators can be transformed back to Malmquist indices. By applying the relation between the directional distance function and the classical distance function stated in equation (1.6), I obtain the following indexes:

$$\begin{aligned} PC_t^{t+1} \quad &= \quad \left[\frac{1 + \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \overrightarrow{D}_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})} \cdot \frac{1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})}\right]^{1/2}, \\ EC_t^{t+1} \quad &= \quad \frac{1 + \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})}, \\ TC_t^{t+1} \quad &= \quad \left[\frac{1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)}{1 + \overrightarrow{D}_o^t(\mathbf{x}^t, \mathbf{y}^t, \mathbf{b}^t)} \cdot \frac{1 + \overrightarrow{D}_o^{t+1}(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})}{1 + \overrightarrow{D}_o^t(\mathbf{x}^{t+1}, \mathbf{y}^{t+1}, \mathbf{b}^{t+1})}\right]^{1/2}. \end{aligned} \tag{1.15}$$

Difference-in-Log-Distance Approach

Another approach to measure productivity and efficiency change is to compute differences in log distances (Agee, Atkinson, and Crocker, 2008). I estimate the output directional distance function

$$0 = \overrightarrow{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) + \beta_i f_i + \epsilon_{it}*, \tag{1.16}$$

where

$$\epsilon_{it}* = v_{it} - u_{it} - \beta_i f_i. \tag{1.17}$$

The term u_{it} is a one-sided error, measuring firm-specific technical inefficiency, and v_{it} is a random noise term. Since I want to measure PC, EC, and TC in terms of percentage changes, following the relation between the directional distance function and the classical distance function in equation (1.6), I transform the output directional distance function into the output distance function. The distance function is expressed as

$$\begin{aligned} 1 &= D_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) exp(v_{it} - u_{it}) \\ &= D_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) exp(\beta_i f_i) exp(\epsilon_{it}*). \end{aligned} \tag{1.18}$$

Taking logs of equation (1.18) and using fitted values, I obtain

$$0 = ln\hat{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) + \hat{\beta}_i f_i + \hat{\epsilon}_{it} * . \tag{1.19}$$

Rearranging the terms in equation (1.19), I obtain

$$\hat{u}_{it} - \hat{v}_{it} = ln\hat{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}). \tag{1.20}$$

I compute the fitted directional distance by setting β_i=0 in (1.16), and then using the relation in (1.6) to obtain the fitted value for the distance function, $\hat{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it})$. I define $\omega_{it} = \hat{u}_{it} - \hat{v}_{it}$. To obtain a consistent estimator of u_{it}, I regress ω_{it} on a set of firm dummies, f_i, and the interactions of firm dummies with time:

$$\omega_{it} = \delta_0 + \delta_i f_i + \sum_t \delta_{it} f_i t + \sigma_{it}. \tag{1.21}$$

The fitted values, $\tilde{u}_{it}$, from this regression are consistent estimators of $\hat{u}_{it}$.

Next, to give the estimated directional distance economic meaning, I restrict $\tilde{u}_{it} > 0$ by adding and subtracting $\tilde{u}_t$ from the fitted version of $ln\hat{D}^t_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) + \hat{v}_{it} - \tilde{u}_{it}$, where $\tilde{u}_t \equiv \min_i\{\hat{u}_{it}\}\forall t$.

$$\begin{aligned} 0 &= ln\hat{D}^t_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) + \hat{v}_{it} - \tilde{u}_{it} + \tilde{u}_t - \tilde{u}_t \\ &= ln\hat{D}^t_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) - \tilde{u}_t + \hat{v}_{it} - (\tilde{u}_{it} - \tilde{u}_t) \\ &= ln\hat{D}^{F,t}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) + \hat{v}_{it} - \tilde{u}^F_{it}. \end{aligned} \tag{1.22}$$

Therefore, technical efficiency, TE_{it}, can be estimated as

$$TE_{it} = exp(-\tilde{u}^F_{it}). \tag{1.23}$$

Efficiency change, EC_{it}, then is computed as

$$EC_{it} = \triangle TE_{it} = TE_{i,t+1} - TE_{it}. \tag{1.24}$$

Technical change, TC_{it}, can be estimated by computing the difference between $ln\hat{D}^{F,t+1}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it})$ and $ln\hat{D}^{F,t}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it})$, holding input and output quantities constant:

$$\begin{aligned} TC_{it} &= ln\hat{D}^{F,t+1}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) - ln\hat{D}^{F,t}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) \\ &= (ln\hat{D}^{t+1}_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) - \tilde{u}_{t+1}) - (ln\hat{D}^t_o(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}) - \tilde{u}_t). \end{aligned} \tag{1.25}$$

Finally, I obtain PC_{it} as

$$PC_{it} = EC_{it} + TC_{it}. \tag{1.26}$$

1.2.4 Model Specifications

Quadratic Output Directional Distance Model

Recall the directional output distance function in equation (1.5), $\overrightarrow{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}, \mathrm{t}; \mathrm{g}_y, -\mathrm{g}_b) = \sup\{(\beta : (\mathbf{y} + \beta\, \mathrm{g}_y, \mathbf{b} - \beta\, \mathrm{g}_b) \in \mathrm{P}(\mathbf{x}, \mathbf{y}, \mathbf{b}, \mathrm{t})\}$, where the input vector $\mathbf{x}=(\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3)$ includes capital, labor, and energy; the good output vector $\mathbf{y}=(\mathrm{y}_1, \mathrm{y}_2)$ refers to electricity generation that is sold for residential and commercial/industrial use; and the bad output vector $\mathbf{b}$=(b_1, b_2, b_3) measures CO_2, SO_2, and NO_X emissions. Before estimating the output directional distance function, I standardize all the variables so they are unit free. I choose the direction vector as (g_x, g_y, g_b)=(0,1,-1) since the production objective is to increase the good outputs and reduce the bad outputs. The choice of the direction vector is consistent with previous studies on this subject (e.g. Chung, Färe, Grosskopt, 1997).

A quadratic form of the directional output distance function can be written as:

$$\begin{aligned}
\overrightarrow{D}_o(\mathbf{x}, \mathbf{y}, \mathbf{b}; 0, 1, -1) \;\; = \;\; & \alpha_0 + \sum_{n=1}^{N} \alpha_n x_n + \sum_{g=1}^{G} \beta_g y_g + \sum_{\omega=1}^{B} \phi_\omega b_\omega \\
& + \frac{1}{2} \sum_{n=1}^{N} \sum_{n\prime=1}^{N} \alpha_{nn\prime} x_n x_{n\prime} + \frac{1}{2} \sum_{g=1}^{G} \sum_{g\prime=1}^{G} \beta_{gg\prime} y_g y_{g\prime} + \frac{1}{2} \sum_{\omega=1}^{B} \sum_{\omega\prime=1}^{B} \phi_{\omega\omega\prime} b_\omega b_{\omega\prime} \\
& + \sum_{g=1}^{G} \sum_{n=1}^{N} \gamma_{gn} y_g x_n + \sum_{\omega=1}^{B} \sum_{n=1}^{N} \delta_{\omega n} b_\omega x_n + \sum_{g=1}^{G} \sum_{\omega=1}^{B} \theta_{g\omega} y_g b_\omega. \qquad (1.27)
\end{aligned}$$

To satisfy the translation property in (p5), the following restrictions must be imposed:

$$\begin{aligned}
\sum_{g=1}^{G} \beta_g - \sum_{\omega=1}^{B} \phi_\omega &= -1, \\
\sum_{g=1}^{G} \beta_{gg\prime} - \sum_{\omega=1}^{B} \theta_{\omega g\prime} &= 0, \; \forall\, g, \\
\sum_{g=1}^{G} \gamma_{gn} - \sum_{\omega=1}^{B} \delta_{\omega n} &= 0, \; \forall\, n, \\
\sum_{g=1}^{G} \theta_{g\omega} - \sum_{\omega=1}^{B} \phi_{\omega\omega} &= 0, \; \forall\, \omega. \qquad (1.28)
\end{aligned}$$

Symmetry must also be imposed:

$$\begin{aligned}
\alpha_{nn\prime} &= \alpha_{n\prime n}, \; \forall\, n, n\prime, \\
\beta_{gg\prime} &= \beta_{g\prime g}, \; \forall\, g, g\prime, \\
\phi_{\omega\omega\prime} &= \phi_{\omega\prime\omega}, \; \forall\, \omega, \omega\prime, \\
\gamma_{gn} &= \gamma_{ng}, \; \forall\, n, \\
\delta_{\omega n} &= \delta_{n\omega}, \; \forall\, n, \omega, \\
\theta_{g\omega} &= \theta_{\omega g}, \; \forall\, \omega. \qquad (1.29)
\end{aligned}$$

In this paper, 3 good inputs, 2 good outputs, and 3 undesirable outputs are modeled, so that N=3, G=2, and B=3.

Input Distance Function with Emissions as Technology Shifters

To evaluate the measurements of PC, EC, and TC based on the directional distance function, I also estimate the input distance function approach for comparison. One way to incorporate the environmental effects of emissions into the model is to treat them as control variables or technology shifters (Atkinson and Dorfman, 2005); other approaches include treating the bad outputs as inputs or redefining the bad outputs as good outputs. I apply the first approach to estimate an input distance function using a translog functional form, treating emissions as technology shifters. The model to be estimated can be written as:

$$\begin{aligned} D_i(\mathbf{x},\mathbf{y},t) &= \alpha_0 + \sum_{n=1}^{N}\alpha_n lnx_n + \sum_{g=1}^{G}\beta_g lny_g + \sum_{\omega=1}^{B}\phi_\omega lnb_\omega \\ &+\frac{1}{2}\sum_{n=1}^{N}\sum_{n\prime=1}^{N}\alpha_{nn\prime} lnx_n lnx_{n\prime} + \frac{1}{2}\sum_{g=1}^{G}\sum_{g\prime=1}^{G}\beta_{gg\prime} lny_g lny_{g\prime} \\ &+\frac{1}{2}\sum_{\omega=1}^{B}\sum_{\omega\prime=1}^{B}\phi_{\omega\omega\prime} lnb_\omega lnb_{\omega\prime} + \sum_{g=1}^{G}\sum_{n=1}^{N}\gamma_{gn} lny_g lnx_n \\ &+\sum_{\omega=1}^{B}\sum_{n=1}^{N}\delta_{\omega n} lnb_\omega lnx_n + \sum_{g=1}^{G}\sum_{\omega=1}^{B}\theta_{g\omega} lny_g lnb_\omega. \end{aligned} \tag{1.30}$$

To impose the property of linear homogeneity in input quantities, I need the following parametric restrictions:

$$\begin{aligned} \sum_{n=1}^{N}\alpha_n &= 1, \\ \sum_{n}^{N}\sum_{n\prime}^{N}\alpha_{nn\prime} &= 0, \\ \sum_{n=1}^{N}\gamma_{gn} &= 0,\ \forall\ g, \\ \sum_{n=1}^{N}\delta_{\omega n} &= 0,\ \forall\ \omega. \end{aligned} \tag{1.31}$$

Symmetry restrictions similar to those in equation (1.29) are also imposed. After I estimate the input distances, I can then apply the index-number approach and the difference-in-log-distances approach to obtain measures of PC, TC, and EC.

1.3 Data Description

1.3.1 List of Utilities in This Study

In this study, I analyze data on 78 U.S. privately owned utilities that produce electricity with fossil-fuel steam-generating technology. My sample comprises the leading privately owned firms in this industry. The sample period from 1988 to 2005 covers the introduction of major environmental regulatory changes, including the establishment of SO_2 and NO_X cap-and-trade systems in 1996 and 1999, respectively. Table (1.2) lists the 78 electric utilities and their operating status. Since the late 1990s, 28 out of the 78 firms stopped steam electricity generation. This industry-wide structural change took place mostly between 1998 and 2002. The year of a firm's change in status is indicated in parentheses. For example, Central Illinois Public Service Co. sold and shut down its steam electricity-generating assets and has not generated electricity since 2001. However, the firm is still operating as an electricity distributor and wholesaler. Interstate Power Co. merged with Interstate Power and Light Co. in 2002, and data are available only for the merged company since then. Therefore, I indicate this as missing data for Interstate Power Co. since the year 2002. San Diego Gas and Electric Co., which is also indicated as missing data since 2000, aborted its steam electricity generation in 2000, but retained its nuclear electricity generation production and continued to provide and distribute electricity. All of these changes in firms' production status reflect their response to changes in production costs and benefits over a period during which the environmental regulations on pollution abatement standards substantially reduced fossil-fueled production.

Table 1.2: List of the Utilities in This Analysis

Order	Utility	Producer	Distributor Only	Shut Down
1	Alabama Power Co.	x		
2	Central Illinois Public Service Co.		x (2001)	
3	Union Electric Co.	x		
4	Appalachian Power Co.	x		
5	Arizona Public Service Co.	x		
6	Atlantic City Electric Co.	x		
7	Baltimore Gas and Electric Co.		x (2001)	
8	Boston Edison Co.		x (1999)	
9	Carolina Power and Light Co.	x		
10	Central Hudson Gas and Electric Corp.		x (2002)	
11	Central Maine Power Co.		x (1999)	
12	Central Power and Light Co.		x (2002)	
13	Cincinnati Gas and Electric Co.	x		
14	Central Louisiana Electric Co., Inc.	x		
15	Cleveland Electric Illuminating Co.	x		
16	Columbus Southern Power Co.	x		
17	Commonwealth Edison Co.		x (2000)	
18	Consolidated Edison Co. of NY	x		
19	Dayton Power and Light Co.	x		
20	Delmarva Power and Light Co.		x (2002)	
21	Detroit Edison Co.	x		
22	Duke Power Co.	x		
23	Duquesne Light Co.		x (2000)	
24	Entergy Arkansas, Inc.	x		
25	Entergy Gulf States, Inc.	x		

Order	Utility	Producer	Distributor Only	Shut Down
26	Entergy Louisiana, Inc.	x		
27	Entergy Mississippi, Inc.	x		
28	Entergy New Orleans, Inc.	x		
29	Florida Power and Light Co.	x		
30	Florida Power Corp.	x		
31	Georgia Power Co.	x		
32	Gulf Power Co.	x		
33	Houston Lighting and Power Co.		x (2002)	
34	Illinois Power Co.		x (1999)	
35	Indiana Michigan Power Co.	x		
36	Indianapolis Power and Light Co.	x		
37	Interstate Power Co.	x	missing data(02)	
38	Kansas City Power and Light Co.	x		
39	Kentucky Utilities Co.	x		
40	KGE, A Western Resources Company	x		
41	Long Island Lighting Co.		x (2001)	
42	Louisville Gas and Electric Co.	x		
43	Minnesota Power and Light Co.	x		
44	Mississippi Power Co.	x		
45	Montana Dakota Utilities Co.	x		
46	Montana Power Co.			x (2002)
47	New England Power Co.		x (1999)	
48	New York State Electric and Gas Corp.		x (1999)	
49	Niagara Mohawk Power Corp.		x (2002)	
50	Northern Indiana Public Service Co.	x		
51	Northern States Power Co.	x		
52	Ohio Edison Co.		x (2001)	
53	Ohio Power Co.	x		

Order	Utility	Producer	Distributor Only	Shut Down
54	Oklahoma Gas and Electric Co.	x		
55	Pacific Gas and Electric Co.	x		
56	PacifiCorp West and East	x		
57	PECO Energy Co.		x (2001)	
58	Pennsylvania Power and Light Co.		x (2000)	
59	Potomac Edison Co.		x (2002)	
60	Potomac Electric Power Co.		x (2001)	
61	PSC of Colorado	x		
62	PSC of New Hampshire	x		
63	PSC of New Mexico	x		
64	PSI Energy, Inc.	x		
65	Public Service Electric and Gas Co.		x (2001)	
66	Rochester Gas and Electric Corp.	x		
67	San Diego Gas and Electric Co.		x (2000)	
68	South Carolina Electric and Gas Co.	x		
69	Southern California Edison Co.	x		
70	Southwestern Electric Power Co.	x		
71	Southwestern Public Service Co.	x		
72	Tampa Electric Co.	x		
73	Texas Utilities Electric Co.		x (2002)	
74	United Illuminating Co.		x (2000)	
75	Virginia Electric and Power Co.	x		
76	West Penn Power Co.		x (2001)	
77	Wisconsin Electric Power Co.	x		
78	Wisconsin Public Service Corp.	x		

Table (1.3) reports the summary statistics of the variables used in this analysis, computed from annual data over 1988–2005 across the 78 firms. Since I exclude observations with missing values or 0 for electricity outputs, I employ a subsample of 1266 out of 1404 observations only for those firms with positive values for quantity of steam electricity generation, STMQ, and for expenditures on capital, EXPK. The firms' production data were collected from FERC Form-1. The inputs and good outputs are defined following Christensen and Jorgenson (1973, 1996) and Atkinson, Cornwell, and Honerkamp (2003). The emissions are computed in accordance with the methodology described in the EIA Electric Power Annual. Appendix A contains a detailed discussion of the construction of my dataset, including data sources and the computational approach.

Table 1.3: Descriptive Statistics of Sample Variables

Variable	Mean	Std Dev	Description
TIME	8.83254	4.99996	18 years (1988–2005)
QE	1.97290D+08	1.62691D+08	quantity of energy (MMBtu)
EXPE	30536.09992	26171.57736	expenditure on energy ($10,000)
PL	41091.03177	23634.87429	price of labor ($ per worker)
EXPL	4599.88880	4233.56731	expenditure on labor ($10,000)
STMQ	1727.24521	1344.40470	quantity of steam electricity generation (10,000 MWh)
NETQ	2423.31156	1978.92766	net electricity generation (10,000 MWh)
QOTH	696.06635	1073.54940	electricity generated by other methods (10,000 MWh)
QPUR	1320.78867	1940.24793	quantity of electricity purchased (10,000 MWh)
PSTMQ	0.76805	0.22737	percentage of steam generation in net generation

Variable	Mean	Std Dev	Description
VINT	26.81908	6.27154	firm vintage index (years)
YIELD	0.081532	0.012808	latest issued long-term bond yield
EXPK	10084.73729	7447.70626	expenditure on capital ($10,000)
QW	685.93681	1485.49058	quantity of wholesale (10,000 MWh)
SALR	807.96104	770.02962	quantity of residential sales (10,000 MWh)
SALI	777.89941	696.30241	quantity of industrial sales (10,000 MWh)
SALC	776.23662	794.67826	quantity of commercial sales (10,000 MWh)
REVW	24305.96261	51800.84081	wholesale revenues ($10,000)
REVR	69929.42631	72528.95940	residential sales revenues ($10,000)
REVI	37416.08127	34575.51797	industrial sales revenues ($10,000)
REVC	59565.47844	72917.80072	commercial sales revenues ($10,000)
TOTSO2	111990.01949	124091.35684	SO_2 emissions (tons)
TOTCO2	1.79349D+07	1.45215D+07	CO_2 emissions (tons)
TOTNOX	52587.02115	43954.74804	NO_X emissions (tons)
HWI	330.10664	44.05235	Handy-Whitman Index (base year = 1973)

Input variables include energy, labor, and capital. Quantity of energy measures the total heat content in MMBtus from all types of fossil-fuel inputs in every plant of each firm. Expenditure on energy refers to the total amount of money a firm spent on all of its fossil fuel inputs in a given year. Price of labor is obtained by dividing the total annual expenditure on labor by the number of employees, reported at the end of each year. Capital expenditure is defined and computed based on information on firms' long-term debt interest payments, debt/equity ratio, depreciation expenses, and the value of plant assets as indicated in the

FERC Form-1. Price of capital is defined as the product of the Handy-Whitman Index for electricity construction costs and the yield on firms' latest issue of long-term debt.

Output variables include good output, which is electricity generated for residential and commercial/industrial use by fossil-fuel steam-generating technology, and bad outputs, SO_2, CO_2, and NO_X emissions. For electricity output, I also collect data on sales revenues from electricity sold to residential, commercial/industrial, and wholesale consumers. This helps to account for the differences in the demand and supply conditions in separate markets for electricity. For example, the price elasticities of demand and of supply are different for a firm that mainly supplies electricity for industrial uses and a firm that mainly supplies electricity to residential customers.

In addition, to control for the age of the electricity-generating assets and firms' capital turnover rates, I include vintage index data for each of the 78 firms in this study. The vintage index is the average of plant age, weighted by the plant's share of total steam-generating capacity within a given firm. It reflects cumulative changes in the age of electricity-generation assets of utility-firms' plants. That is, when a firm retires an old plant or builds a new plant for electricity generation, the firm's vintage index will decrease. If a firm does not adjust any of the electricity generation assets in any of its plants in a given year, this firm's vintage index will go up by 1 compared to the previous year.

Finally, I collect data on firm net electricity generation, which is the total electricity output generated by fossil-fuel steam-generation technology, nuclear technology, hydropower, and all other methods. By subtracting the fossil-fuel steam electricity output from the net output, I can control for the quantity of electricity output generated by other methods in each firm. Many of these firms, such as Union Electric Co., only have fossil-fuel steam electricity output such that their net output equal their steam electricity output. However, other firms rely on more than one method of electricity generation. For instance, Rochester Electric Gas and Electric Corp. has both fossil-fuel steam electricity generation and nuclear generation plants. Its fossil-fuel steam-generated electricity output—measured in 10,000 MWh—

decreased from around 220 to 150 in 1993, then decreased again to only 98 in 2005; its net output, however, remained at a constant level because its nuclear electricity output gradually increased over time.

In table (1.4), I compute the annual total energy used, outputs, and emissions for the 78 firms. The units of the quantities are consistent with those in table (1.3). Figure (1.2), (1.3), and (1.4) summarize table (1.4). Figure (1.2) plots the trend of total quantity of energy and the number of firms in the sample. The total quantity of energy used in these firms were relatively stable between 1988 to 1993, then increased slightly in the subsequent years until 1998. In 1999 and 2000 there was a significant decrease in energy usage and outputs; then they became stable again at lower levels from 2003 to 2005. This trend may have resulted from the more stringent environmental regulations and the development of new and cleaner energy resources.

Table 1.4: Trends of Fuel Consumption, Electricity Output, and Emissions

Year	Num of firms	QE[a]	STMQ	QOTH	QPUR[b]	SO_2	CO_2	NO_X[c]
1988	78	143.402	12.749	4.282	5.204	10.428	1241.535	4.498
1989	78	145.758	13.237	4.323	5.380	11.013	1294.866	4.693
1990	78	143.060	12.840	4.778	6.231	10.753	1259.478	4.474
1991	78	141.666	12.710	5.010	7.382	10.551	1248.404	4.406
1992	78	142.066	12.670	4.976	7.577	10.290	1240.169	4.276
1993	78	145.369	12.994	5.327	8.229	10.124	1277.065	4.361
1994	78	150.125	13.077	5.413	8.349	9.517	1278.494	4.163
1995	78	149.760	13.015	5.795	9.084	7.782	1268.238	4.084
1996	78	153.880	13.408	5.685	9.903	8.286	1329.309	4.330
1997	78	159.955	13.872	5.344	10.789	8.548	1380.148	4.447
1998	77	165.170	14.178	5.563	10.974	7.851	1568.176	4.430
1999	73	157.662	13.317	5.945	11.217	6.973	1502.516	4.174
2000	64	143.034	12.053	4.635	10.069	5.873	1381.210	3.761
2001	60	120.020	10.807	4.291	14.439	5.049	1156.124	2.009
2002	53	108.501	9.422	4.090	9.746	4.581	1053.492	1.879
2003	53	105.220	9.484	4.106	9.928	4.511	1038.845	1.835
2004	53	108.847	9.454	4.219	11.129	4.655	1068.780	1.975
2005	53	113.624	9.622	4.391	11.462	4.913	1112.875	2.774

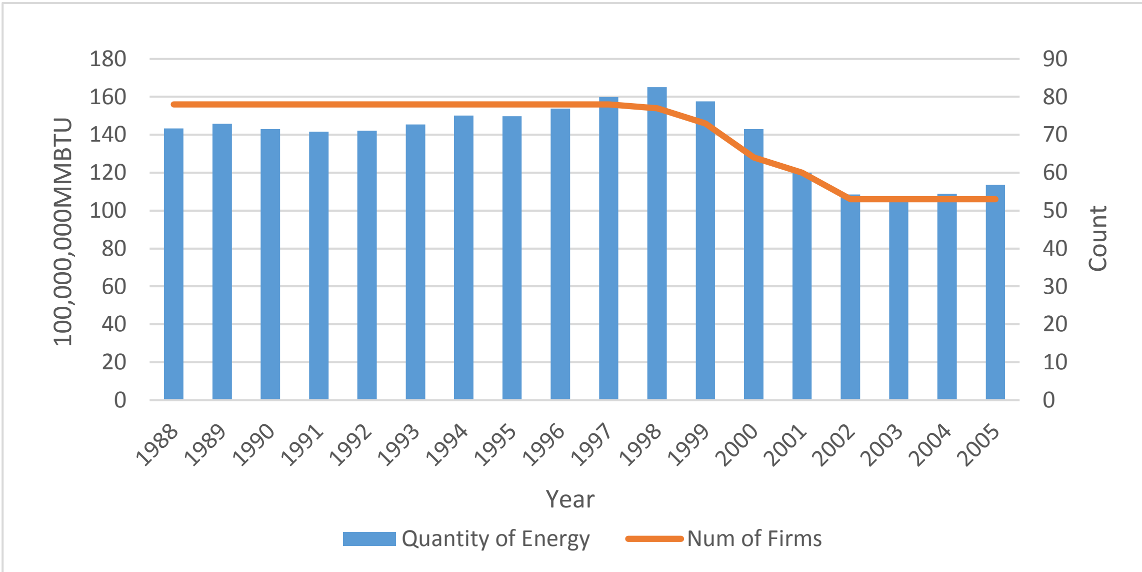
[a] QE is reported in 100,000,000 MMBtu.

[b] STMQ, QOTH, and QPUR are reported in 100,000,000 MWh.

[c] Emissions of SO_2, CO_2, and NO_X are reported in 1,000,000 tons.

Figure (1.3) summarizes electricity output by steam-generated electricity, non-steam generated electricity, and purchased electricity. The quantity of electricity output began to

Figure 1.2: Total Quantity of Energy Consumption of Utility Firms, 1988-2005



decline for steam generation since 2000, but stable for non-steam generation. Meanwhile, firms relied more and more on purchased electricity.

Figure 1.3: Total Electricity Output of Utility Firms, 1988-2005

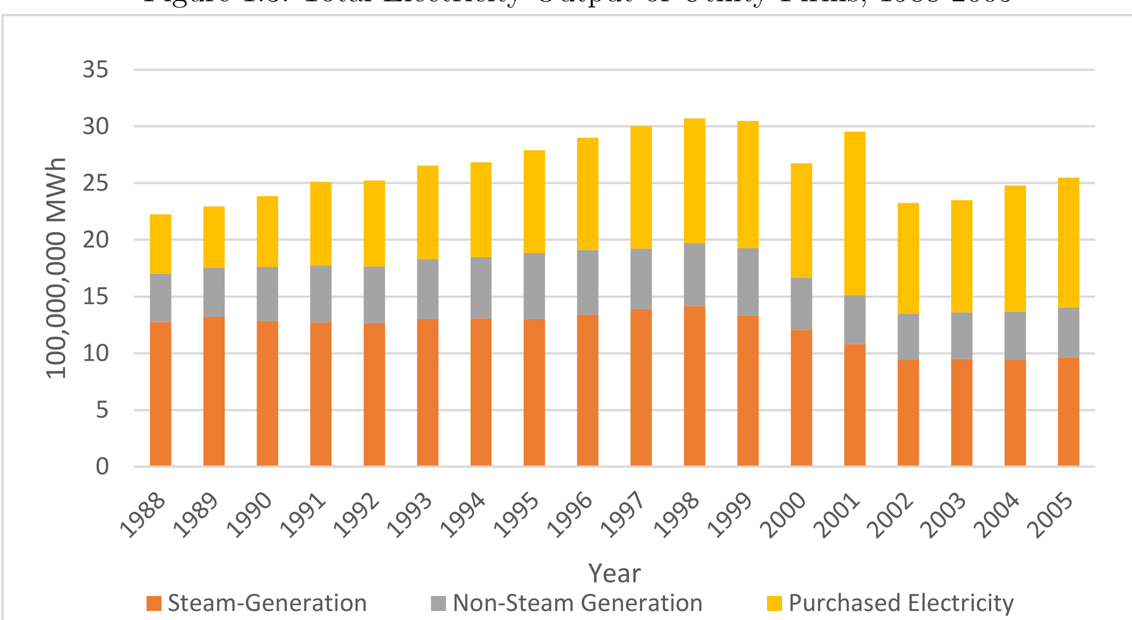
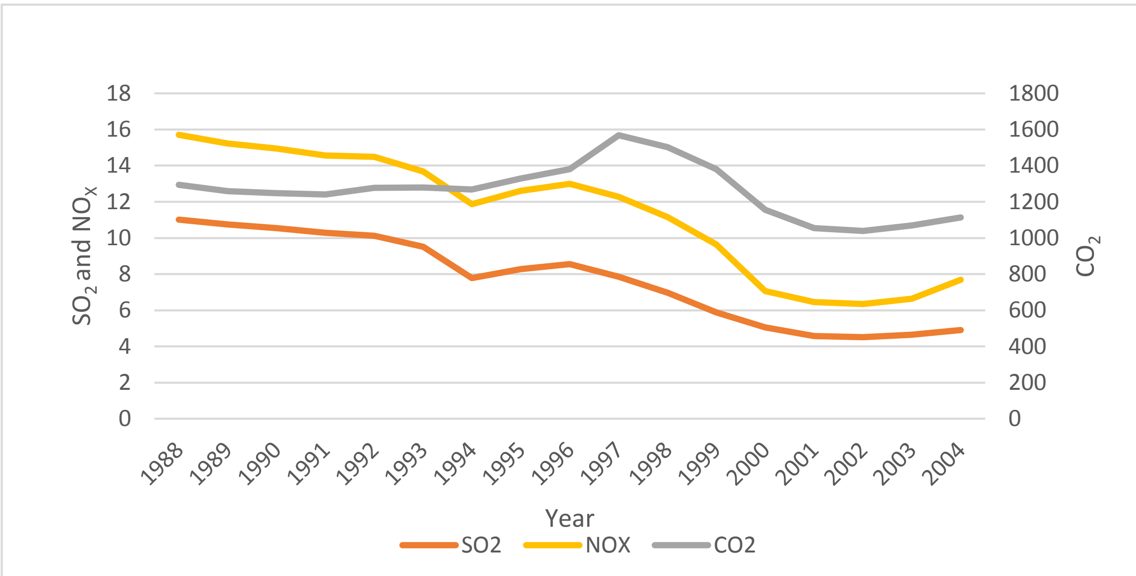


Figure (1.4) shows the trend of total emissions. Since the cap-and-trade system was established in the U.S. for SO_2 and NO_X emissions in 1996 and 1999, respectively, we observe a significant decrease in SO_2 emissions since 1995 and in NO_X since 2000. However, CO_2 emissions are not yet regulated and have remained relatively stable over time, decreasing only slightly as output has fallen.

Figure 1.4: Total Emissions of Utility Firms, 1988-2005

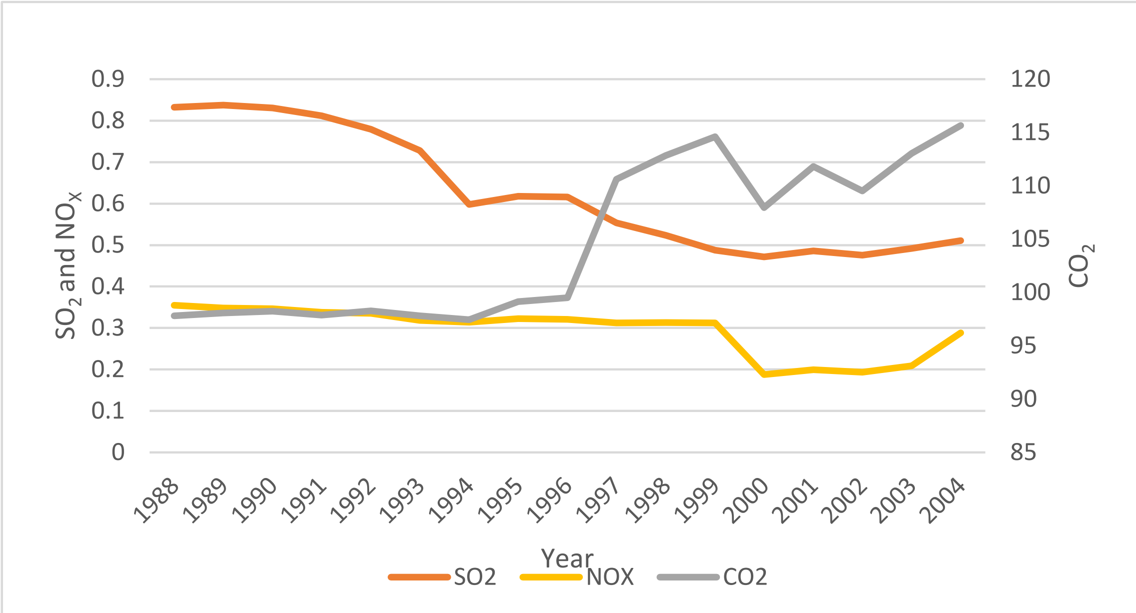


In table (1.5), I compute the emissions per unit of output to control for variable output levels over time. Figure(1.5) summarizes table (1.5). A clearly decreasing trend in the emissions per unit of output indicates that these firms have made progress in pollution control. Emissions of SO_2 were 0.0082 tons per MWh of electricity in 1988. This figure fluctuated for a few years, then began to decrease in 1993, dropping dramatically each year until 2001. Then this figure became relatively stable and low at around 0.0048 tons per kWh of electricity output. Since CO_2 emissions are not regulated in the United States, the level of emissions per unit of output remained quite stable and high at around 0.98 tons per unit of output from 1988 to 1997, then increased to around 1.1 tons per unit of outputs since 1998. Similar to SO_2 emissions, the level of CO_2 emissions per MWh of electricity stayed relatively stable in the last few years of my sample. Finally, NO_X emissions gradually declined over time, with significant decreases in 2001. This clearly reflects the effect of the 1999 policy change that established the cap-and-trade system for NO_X emissions.

Table 1.5: Annual Emissions Per Unit of Output (0.01tons/MWh)

Year	Number of firms	SO_2	CO_2	NO_X
1988	78	0.8179	97.3824	0.3528
1989	78	0.8320	97.8218	0.3548
1990	78	0.8375	98.0887	0.3485
1991	78	0.8302	98.2257	0.3467
1992	78	0.8122	97.8801	0.3375
1993	78	0.7791	98.2822	0.3356
1994	78	0.7280	97.7971	0.3185
1995	78	0.5979	97.4439	0.3138
1996	78	0.6180	99.1401	0.3229
1997	78	0.6162	99.4904	0.3206
1998	77	0.5537	110.6098	0.3125
1999	73	0.5236	112.8276	0.3134
2000	64	0.4872	114.5911	0.3120
2001	60	0.4715	107.9636	0.1877
2002	53	0.4862	111.8066	0.1994
2003	53	0.4756	109.5309	0.1934
2004	53	0.4923	113.0469	0.2089
2005	53	0.5106	115.6583	0.2883

Figure 1.5: Total Emissions Per Unit of Output



1.4 Empirical Results

1.4.1 PC, EC, and TC Measured by the Directional Distance Functions

This study builds on previous research by examining annual production data with three types of emissions over a longer and more recent time period. Previous studies either ignore emissions in their production models or consider only SO_2 or NO_X emissions. I compare regression results from four models: a regression ignoring emissions, a regression with SO_2 emission only, a regression with both SO_2 and NO_X emission, and a regression with all three types of emissions. The first two regressions are similar to those reported in the previous studies. The third regression is motivated by the fact that within the sample period only SO_2 and NO_X are subject to environmental regulations, the Acid Rain Program. In my last equation I include CO_2 emissions as well. In all regressions I specify the direction for the good outputs to be 1 and the bad outputs to be -1 within the output directional distance function model.

Before estimating the quadratic output directional distance functions, I standardize each variable by subtracting its mean and then dividing by the standard deviation so that each variable is unit free in the model. I estimate the following fixed-effect model by using least squares:

$$0 = \vec{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}; 0, 1, -1) + f_i + \tau_t + vint_{it} + vint_{it}^2 + qoth_{it} + \epsilon_{it}, \tag{1.32}$$

where $\mathbf{x}_{it}, \mathbf{y}_{it}, and\ \mathbf{b}_{it}$ are inputs, good outputs, and emissions, respectively; f_i is a set of firm dummies that measure firm-specific inefficiency; τ_t is a set of time dummies to capture the time effect; $vint_{it}$ is the vintage index that controls for the age of firms' steam electricity-generating assets or capital turnover rate; $qoth_{it}$ is the quantity of electricity output produced by a non-steam technology; and ϵ_{it} is random noise. The output directional distance function, following (1.27), is written as:

$$\begin{aligned}
\vec{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}; 0, 1, -1) \quad = \quad & \alpha_0 + \sum_{n=1}^{3} \alpha_n x_{n,it} + \sum_{g=1}^{2} \beta_g y_{g,it} + \sum_{\omega=1}^{3} \phi_\omega b_{\omega,it} \\
& + \frac{1}{2} \sum_{n=1}^{3} \sum_{n\prime=1}^{3} \alpha_{nn\prime} x_{n,it} x_{n\prime,it} + \frac{1}{2} \sum_{g=1}^{2} \sum_{g\prime=1}^{2} \beta_{gg\prime} y_{g,it} y_{g\prime,it} \\
& + \frac{1}{2} \sum_{\omega=1}^{3} \sum_{\omega\prime=1}^{3} \phi_{\omega\omega\prime} b_{\omega,it} b_{\omega\prime,it} + \sum_{g=1}^{2} \sum_{n=1}^{3} \gamma_{gn} y_{g,it} x_{n,it} \\
& + \sum_{\omega=1}^{3} \sum_{n=1}^{3} \delta_{\omega n} b_{\omega,it} x_{n,it} + \sum_{g=1}^{2} \sum_{\omega=1}^{3} \theta_{g\omega} y_{g,it} b_{\omega,it}.
\end{aligned} \tag{1.33}$$

Choosing a fixed-effect over a random-effect specification allows the firm-specific effects to be correlated with other regressors, such as input and output levels. For example, firm-specific characteristics such as plant location can be correlated with input variables like the price of labor, fuel quality, and so on.

Tables (1.6) and (1.7) present the estimated coefficients of all four regressions, following equation (1.32). The coefficients on the firm and time dummies are omitted from the tables for simplicity. The second column in table (1.6), regression (1), reports the results from estimating the directional distance functions omitting all emissions. The third column, regression (2), shows the estimates considering SO_2 emissions only, and crediting firms that reduce their levels of SO_2 emissions. Similarly, in table (1.7) regression (3) adds NO_X and its second-order and interaction terms with other input and output variables. Finally, regression (4) shows the estimation results of the full model specification where all three types of emissions are included in the directional distance function. The estimated coefficients from these four regressions are mostly consistent in terms of sign and magnitude with only a few exceptions on interaction terms and second-order terms. Therefore, the effects of adjusting inputs or outputs, as well as emissions, on the estimated directional distance functions or the measure of efficiency are negligible across these different model specifications. In addition, the estimated coefficients are properly signed and consistent with intuition and the definition of the output directional distance function. That is, the directional distance increases—indicating lower technical efficiency—when firms increase their inputs, decrease their good outputs, or increase their emissions.

Table 1.6: Fixed-Effect Estimation: Output Directional Distance Model

Variable	Coefficient (t-stat)	
	Reg (1)	Reg (2)
Intercept	-0.480 (-9.124)**	-0.332 (-7.240)**
Capital	0.109 (9.439)**	0.077 (7.575)**
Capital^2	-0.044 (-3.660)**	-0.001 (-0.077)
Energy	0.259 (14.649)**	0.240 (15.629)**
Energy^2	0.039 (3.219)**	-0.179 (-10.325)**
Labor	-0.015 (-1.499)	-0.014 (-1.661)
Labor^2	-0.004 (-1.263)	-0.003 (-1.030)
Capital*Labor	-0.006 (-0.866)	-0.005 (-0.858)
Capital*Energy	0.031 (3.168)**	0.021 (2.133)**
Labor*Energy	0.015 (2.130)**	0.016 (2.055)**
Electricity_Res	-0.241 (-14.493)**	-0.203 (-12.368)**

Variable	Coefficient (t-stat)	
	Reg (1)	Reg (2)
Electricity_Res^2	0.163 (12.068)**	0.097 (5.829)**
Electricity_I&C	-0.759 (-45.658)**	-0.688 (-40.829)**
Electricity_I&C^2	0.163 (12.068)**	0.179 (13.906)**
Electricity_Res*Electricity_I&C	-0.163 (-12.068)**	-0.155 (-12.126)**
Energy*Electricity_I&C	0.122 (11.456)**	0.144 (11.927)**
Labor*Electricity_I&C	0.006 (0.630)	0.015 (1.994)**
Capital*Electricity_I&C	-0.022 (-3.157)**	-0.039 (-6.312)**
Capital*Electricity_Res	0.022 (3.157)**	0.003 (0.427)
Labor*Electricity_Res	-0.006 (-0.630)	-0.015 (-1.865)
Energy*Electricity_Res	-0.122 (-11.456)**	-0.006 (-0.500)
SO_2		0.109 (12.990)**
${SO_2}^2$		-0.034 (-10.823)**
Capital*SO_2		-0.036 (-5.799)**
Energy*SO_2		0.138 (17.815)**
Labor*SO_2		0.001 (0.123)
Electricity_I&C*SO_2		0.024 (3.183)**
Electricity_Res*SO_2		-0.058 (-7.546)**
Electricity_Nonsteam	0.091 (7.530)**	0.066 (6.488)**
Vintage	0.014 (5.474)**	0.009 (4.288)**
Vintage^2	0.000 (-5.841)**	0.000 (-5.290)**

Note: Double asterisk indicates significance at the .05 level

Table 1.7: Fixed-Effect Estimation: Output Directional Distance Model (Continued)

Variable	Coefficient (t-stat)	
	Reg (3)	Reg (4)
Intercept	-0.325 (-7.236)**	-0.333 (-9.241)**
Capital	0.081 (8.052)**	0.053 (6.382)**
Capital^2	0.003 (0.253)	-0.017 (-2.045)**
Energy	0.220 (12.379)**	0.063 (3.115)**
Energy^2	-0.162 (-5.609)**	-0.031 (-0.810)
Labor	-0.016 (-1.806)	-0.013 (-1.794)
Labor^2	-0.002 (-0.841)	0.001 (0.539)
Capital*Labor	0.006 (0.925)	-0.009 (-1.615)
Capital*Energy	0.077 (5.324)**	0.087 (5.595)**
Labor*Energy	0.020 (1.793)	0.047 (3.725)**
Electricity_Res	-0.215 (-12.594)**	-0.232 (-15.368)**
Electricity_Res^2	0.123 (6.211)**	0.148 (7.572)**
Electricity_I&C	-0.652 (-37.535)**	-0.543 (-33.192)**
Electricity_I&C^2	0.151 (11.385)**	0.125 (11.233)**
Electricity_Res*Electricity_I&C	-0.150 (-10.711)**	-0.108 (-8.193)**
Energy*Electricity_I&C	0.160 (8.700)**	0.112 (5.017)**
Labor*Electricity_I&C	0.021 (2.508)**	0.028 (4.052)**
Capital*Electricity_I&C	-0.051 (-7.803)**	-0.038 (-7.019)**
Capital*Electricity_Res	-0.020 (-2.183)**	-0.010 (-1.166)
Labor*Electricity_Res	-0.026 (-3.075)**	-0.035 (-4.580)**
Energy*Electricity_Res	-0.035 (-2.135)**	-0.133 (-6.181)**
SO_2	0.089 (9.757)**	0.059 (7.453)**
${SO_2}^2$	-0.044 (-7.434)**	-0.016 (-2.460)**
Capital*SO_2	-0.029 (-4.338)**	-0.010 (-1.393)

Variable	Coefficient (t-stat)	
	Reg (3)	Reg (4)
Energy*SO_2	0.128 (13.923)**	0.114 (6.984)**
Labor*SO_2	-0.008 (-1.448)	-0.006 (-1.286)
Electricity_I&C*SO_2	0.032 (3.927)**	0.024 (3.007)**
Electricity_Res*SO_2	-0.054 (-6.503)**	-0.078 (-8.727)**
NO_X	0.044 (3.999)**	-0.002 (-0.169)
${NO_X}^2$	-0.026 (-4.169)**	-0.012 (-2.133)**
Capital*NO_X	-0.042 (-4.528)**	-0.024 (-3.116)**
Energy*NO_X	-0.003 (-0.208)	0.124 (5.129)**
Labor*NO_X	0.002 (0.252)	0.008 (1.203)
Electricity_I&C*NO_X	-0.031 (-2.762)**	-0.048 (-4.699)**
Electricity_Res*NO_X	0.027 (2.517)**	-0.011 (-0.909)
SO_2*NO_X	0.022 (3.540)**	0.023 (3.032)**
CO_2		0.168 (11.223)**
${CO_2}^2$		0.302 (11.571)**
Capital*CO_2		-0.014 (-1.540)
Energy*CO_2		-0.260 (-9.630)**
Labor*CO_2		-0.008 (-1.012)
Electricity_I&C*CO_2		0.041 (2.994)**
Electricity_Res*CO_2		0.129 (8.765)**
SO_2*CO_2		-0.062 (-7.142)**
CO_2*NO_X		-0.069 (-4.430)**
Electricity_Nonsteam	0.057 (5.493)**	0.062 (7.337)**
Vintage	0.009 (4.560)**	0.008 (4.484)**
Vintage^2	0.000 (-5.451)**	0.000 (-5.381)**

Note: Double asterisk indicates significance at the .05 level

The coefficients on energy and capital inputs from all regressions are positive and statistically significant. When the quantity of capital goes up, the estimated directional distance increases, indicating that firms are less technically efficient; furthermore, it is increasing at a diminishing rate since the coefficient on capital^2 is negative. Similarly, a rise in energy inputs increases the estimated directional distance, again at a diminishing rate, except in regression (1). In addition, as the data have been standardized, the coefficients are unit-free and comparable across variables. The magnitude of the coefficient on energy inputs is much larger than the coefficient on capital inputs, illustrating that differences in energy inputs have a greater impact on firm efficiency than capital inputs. For example, in regression (1), the coefficient on capital is 0.081 whereas the coefficient on energy is 0.220. A similar pattern for these two coefficients is observed in all other regressions. When all three emissions are included in the model, as in regression (4), energy inputs still have a greater impact than capital inputs on estimated directional distances, although to a lesser degree. As for labor inputs, the estimated coefficients are negative and in very small magnitude, but they are not statistically significant in any regressions. Therefore, changes in labor inputs do not affect firms' technical efficiency level. Because this is not a labor-intensive industry, the difference in labor inputs may not affect firms' production significantly.

The estimated coefficients on good outputs—electricity outputs sold to residential, industrial and commercial use—are negative in all regressions, with much larger t-values than the coefficients on inputs and emissions. These results suggest that changes in the quantity of electricity outputs are the major factor that affects firms' efficiency levels. An increase in the good outputs, *ceteris paribus*, will significantly improve a firm's technical efficiency level.

After I include emissions in the model specifications, the estimates show that reducing SO_2 emissions and CO_2 emissions will improve the efficiency level of the firm. CO_2 emissions in particular, although not yet regulated, show a significant effect on efficiency level. The estimated coefficient on NO_X is 0.044 in regression (3), indicating a similar effect to those of SO_2 and CO_2, but it is not significant in regression (4).

The estimated coefficients on vintage imply that when the age of the electricity-generating assets increases, the firm is less technically efficient. Also, the more electricity produced by non-steam-generating methods, such as hydro and nuclear power, the less efficient is a given firm. These coefficients are also statistically significant at the 1% level.

Therefore, for these 78 utility firms from 1988 to 2005, the amounts of electricity sold to industrial and commercial customers and for residential uses has a strong effect on the estimated directional distances. Energy input is the next-most important factor affecting firm efficiency. Pollution control on SO_2 and CO_2 emissions also improves technical efficiency. Last, a reduction in capital inputs and firm vintage indices slightly improves firm efficiency, and the more the firms rely on other electricity-generation methods, such as nuclear and hydro power, the less efficient they are.

The fitted values obtained from the above regressions are the estimated directional distances. Since there is no restriction on non-negativity, I normalize the fitted values by subtracting the minimum from each. These positive values are the output directional distances. The firm with a zero directional distance is the best-practice firm in the sample. Following the above estimations, I obtain fitted values for $\overrightarrow{D}_o^t(\mathbf{x}_{t+1}, \mathbf{y}_{t+1}, \mathbf{b}_{t+1})$, $\overrightarrow{D}_o^{t+1}(\mathbf{x}_t, \mathbf{y}_t, \mathbf{b}_t)$, and $\overrightarrow{D}_o^{t+1}(\mathbf{x}_{t+1}, \mathbf{y}_{t+1}, \mathbf{b}_{t+1})$. I apply both the index-number approach and the difference-in-log-distances approach to measuring firm productivity change and efficiency change. As shown in tables (1.6) and (1.7), the four regressions show consistent and stable results in the directional distance function estimation. Therefore, I compare the two approaches based only on regression (1) and regression (4).

From the estimations of the first regression where emissions are ignored, I derive the annual weighted average of PC, EC, and TC from both approaches. As this is an unbalanced panel data set, the number of firms decreased as some of the firms changed their production status. In table (1.8), reporting results from the Malmquist index approach, the productivity change was about 0.8% in 1989 and 1990, and then decreased in the subsequent two years to only 0.26% in 1992. From 1993 to 1997, productivity grew at over 1% each year. In 1998, two years after the establishment of the SO_2 cap-and-trade system, and as firms adjusted their inputs, average productivity growth was negative. However, beginning in 1999, PC started to grow faster, and the overall annual productivity growth was 1.08% over the period 1988–2005. The productivity growth estimated from the difference-in-log-distances approach shows a very similar pattern but, overall, is slightly lower than the estimated PC from the index-number approach. The estimated efficiency change — or catching-up effect — from the index-number approach is very small over the 18-year period, usually less than 0.1% each year, and negative for the years 1990, 1998 and 2004. The overall annual efficiency change is only 0.245%. From the difference-in-log-distances approach, the overall change is 0.106%, but is fairly stable each year at around 0.1% with no negative growth. Since PC=TC+EC, TC is the major force behind productivity growth. The fluctuation in TC, which is estimated to be 0.8% from the index numbers approach and 0.7% from the difference-in-log-distances approach, determines the change in PC.

Table 1.8: Weighted Average of PC, TC and EC (No Emissions; Weight: STMQ)

		Malmquist Index			Difference-in-log-differences		
Year	Number of Firms	PC	EC	TC	PC	EC	TC
1989	78	1.00845	1.00035	1.00810	0.008009	0.000951	0.007058
1990	78	1.00832	0.99950	1.00883	0.008427	0.000935	0.007492
1991	78	1.00477	1.00152	1.00325	0.005228	0.000947	0.004281
1992	78	1.00264	1.00107	1.00156	0.004234	0.000920	0.003314
1993	78	1.02067	1.00820	1.01236	0.010327	0.000911	0.009416
1994	78	1.01910	1.00091	1.01818	0.013559	0.000886	0.012673
1995	78	1.01658	1.00538	1.01115	0.009681	0.000921	0.008760
1996	78	1.01486	1.00441	1.01040	0.009199	0.000942	0.008257
1997	78	1.01266	1.00342	1.00920	0.008568	0.000967	0.007601
1998	75	0.98794	0.99927	0.98866	-0.002951	0.001118	-0.004069
1999	71	1.01606	1.00175	1.01428	0.011509	0.000982	0.010527
2000	63	1.02044	1.00744	1.01290	0.010759	0.001028	0.009731
2001	58	1.02200	1.00194	1.02003	0.014846	0.000996	0.013850
2002	53	1.00660	1.00052	1.00608	0.007104	0.001471	0.005633
2003	52	1.01219	1.00749	1.00466	0.006362	0.001487	0.004876
2004	52	0.99123	0.98646	1.00484	0.006528	0.001531	0.004997
2005	52	1.01767	1.01157	1.00603	0.007123	0.001516	0.005607
Overall Average[a]		1.01080	1.00245	1.00832	0.008159	0 .001060	0.007100

[a] The arithmetic mean of the yearly indices of PC, EC, and TC.

Next, I derive PC, EC, and TC from my fourth regression, which incorporates the three types of emissions into the directional distance function model. Similarly, for comparison purposes, I apply the Malmquist index approach and the difference-in-log-distances approach. Table (1.9) reports the estimates of weighted averages for PC, EC, and TC. After crediting firms' efforts at emission reduction, from the Malmquist indices, productivity growth is lower than the results in table (1.8), as both the catching-up effect and technical change decrease.

TC started at 0.6% in 1989 and dropped to 0.2% in 1992, then grew faster between 1993 and 1995, at around 1%. From 1996, the annual change in technical efficiency fluctuated around 0.6%, with negative growth in 1998 and 2003. The catching-up effect is very small, with an overall change of only 0.175%. On the other hand, the values of PC, EC, and TC derived from the difference-in-log-distances approach are greater than from the Malmquist index approach without or with emissions. The overall rates of the catching-up effect and technical change are 0.265% and 0.824%, respectively, making the annual productivity growth exceed 1% on average. Technical change was relatively high in 1993, 1994, 1995, and 2001.

Table 1.9: Weighted Average of PC, TC and EC (Consider Emissions; Weight: STMQ)

		Malmquist Index			Difference-in-log-differences		
Year	Number of Firms	PC	EC	TC	PC	EC	TC
1989	78	1.00835	1.00191	1.00643	0.010871	0.0024199	0.008451
1990	78	1.00073	0.99652	1.00423	0.009468	0.0024343	0.007033
1991	78	1.00915	1.00254	1.00659	0.010965	0.0024340	0.008531
1992	78	1.00357	1.00079	1.00277	0.008472	0.0024028	0.006069
1993	78	1.01648	1.00588	1.01054	0.013458	0.0024262	0.011032
1994	78	1.01195	0.99958	1.01238	0.014564	0.0023916	0.012173
1995	78	1.02185	1.00566	1.01610	0.016999	0.0024165	0.014582
1996	78	1.00455	1.00109	1.00346	0.008943	0.0024623	0.006480
1997	78	1.01150	1.00497	1.00650	0.010886	0.0024997	0.008386
1998	75	0.98884	0.99538	0.99344	0.002725	0.0026942	0.000067
1999	71	1.00778	1.00124	1.00653	0.010981	0.0025988	0.008446
2000	63	1.01721	1.01047	1.00668	0.011282	0.0027828	0.008500
2001	58	1.01801	1.00646	1.01147	0.014326	0.0027523	0.011574
2002	53	1.00890	0.99931	1.00960	0.013107	0.0031247	0.009982
2003	52	1.00183	1.00278	0.99906	0.006904	0.0031870	0.003717
2004	52	0.98966	0.98508	1.00465	0.010295	0.0032289	0.007067
2005	52	1.01499	1.01003	1.00491	0.010427	0.0032245	0.007203
Overall Average[a]		1.00796	1.00175	1.00620	0.010870	0.0026543	0.008241

[a] The arithmetic mean of the yearly indices of PC, EC, and TC.

As my above analyses show, the catching-up effect is relatively small, and technical change induces most of the productivity growth over time. One possible reason for this result is that fossil-fuel electric utility firms usually have a long time frame for capital turnover because the fixed costs of building a new plant or adjusting equipment are very high. In addition, switching to alternate fossil-fuel inputs is costly. Since these firms rely heavily on fossil-fuel energy inputs, the geographic location of their plants partly determines the type of fuel used and the quality of their fuel inputs for the plants. Therefore, a less efficient firm will have difficulty catching up with the more efficient ones, and technical change or a shift in the efficient frontier becomes the leading factor behind productivity growth in this industry.

Comparing the results from table (1.8) and (1.9), one can see that the difference-in-log-distances approach shows that, once emissions are incorporated into the model, estimated productivity growth is higher. This is because the first regression does not credit firms for better environmental performance. Furthermore, the catching-up effect is very stable in the second regression. It grows at 0.24% each year for the first 10 years, and then grows at an increasing rate from 1998. With an overall productivity change of around 1% each year, this industry shows a relatively slow productivity growth over time.

Next, following the difference-in-log-distances approach to estimating firms' technical efficiency in equation (1.23), I compute the annual weighted average of firm technical efficiency scores. Two sets of TE scores are reported in table (1.10): one from the model where emissions are ignored and the other from the model in which all three emissions are included. The results clearly show two differences between the two models. First, when emissions are included in the directional distance function model, TE scores are higher. In this model, firms' improvement in environmental performance, i.e., a greater reduction in emissions, is considered to be an increase in technical efficiency. The first model ignores emissions, so it fails to reflect the improvements in pollution control over the years. Second, the estimated technical efficiency scores grow faster in the second model, changing from 0.67725 in 1988 to 0.76452 in 2005; in the first model, TE scores only increase from 0.66339 to 0.71966. Therefore, once emissions are included in the model, one sees improved levels of firm technical efficiency and higher TC over time.

Table 1.10: Average Technical Efficiency Score (Weight: STMQ, by Year)

Year	Number of Firms	TE scores	
		Ignore Emissions	Consider Emissions
1988	77	0.66339	0.67725
1989	77	0.66338	0.67912
1990	77	0.66730	0.68473
1991	77	0.66782	0.68675
1992	77	0.66868	0.68850
1993	77	0.66990	0.69174
1994	77	0.67022	0.69277
1995	77	0.67649	0.70136
1996	77	0.67814	0.70529
1997	77	0.67724	0.70568
1998	75	0.68521	0.71780
1999	72	0.68583	0.72104
2000	67	0.68573	0.72367
2001	59	0.68922	0.72648
2002	52	0.71925	0.75719
2003	51	0.71847	0.75908
2004	51	0.71970	0.76205
2005	51	0.71966	0.76452

I then compute the time-averaged technical efficiency scores of each firm, based on the estimation including all three emissions, and rank the TE scores in table (1.11). Montana Dakota Utilities Co. (MDU, order number 45), with a TE score of 0.94203, is the most efficient of the 78 firms in the study. Following MDU is PSC of New Mexico, with a TE score of 0.92048. The least efficient is Texas Utilities Electric Co., with an average TE score of 0.36523. This firm ceased its fossil-fuel electricity generation in 2002.

Table 1.11: Ranking of Firm Average Technical Efficiency Score

FirmID	Number of Years	TE Score
45	18	0.94203
63	18	0.92048
10	14	0.90256
14	18	0.90247
28	18	0.90097
66	18	0.89300
42	18	0.89274
62	18	0.89218
2	13	0.89093
37	14	0.88936
32	18	0.88553
44	18	0.88457
74	12	0.88315
46	14	0.88049
19	18	0.87599
6	18	0.86959
43	18	0.86860
72	18	0.86402
40	18	0.86123
78	18	0.85873
59	18	0.85487
35	18	0.85437
38	18	0.85379
36	18	0.85110
48	11	0.85034
39	18	0.84752

FirmID	Number of Years	TE Score
20	14	0.84469
27	18	0.84117
11	12	0.83960
50	18	0.83329
70	18	0.83082
13	15	0.82539
34	12	0.82192
71	18	0.82131
5	18	0.81859
16	18	0.81838
41	11	0.81496
23	13	0.81208
24	18	0.81194
68	18	0.80532
8	11	0.79664
15	18	0.79042
64	18	0.78898
67	12	0.78409
54	18	0.78127
76	13	0.77700
77	18	0.76301
12	10	0.75963
61	18	0.75897
31	18	0.75688
30	18	0.75210
4	18	0.74562
52	13	0.74513
3	18	0.72635

FirmID	Number of Years	TE Score
51	18	0.72387
53	18	0.71104
1	18	0.70135
7	13	0.69874
9	18	0.69002
21	18	0.68380
58	13	0.67107
60	14	0.66884
26	18	0.66584
56	18	0.65832
57	13	0.65483
25	18	0.65260
49	14	0.64289
18	18	0.59805
75	18	0.58671
65	13	0.58382
17	12	0.58310
22	18	0.57927
33	10	0.46779
29	18	0.45930
69	18	0.41665
55	18	0.40712
73	14	0.36523

Changes in TE score ranking among the firms over time are also interesting. They tell us whether a firm that started with a high-ranking technical efficiency score remained a relatively efficient firm, or whether the less efficient firms began to catch up with the more efficient ones. These changes also reveal how more stringent environmental policies affect less efficient firms. Do they catch up or are they forced to drop out of the industry? Table (1.12) reports the two sets of results for the most efficient firm, least efficient firm, and median firm from the two regressions.

First, Montana Dakota Utilities Co., the most efficient firm over time, remained the most efficient in both regression results. This is consistent with the overall ranking for the whole time period. Next, the least efficient firm from both regressions, Texas Utilities Electric Co., continued to be the least efficient firm until it stopped fossil-fuel steam electricity generation in 2002 and was dropped from the sample. When the model ignores emission reductions, Florida Power and Light Co. became the least efficient firm in 2002; however, when emissions were included, Pacific Gas and Electric Co. emerged as the least efficient firm in 2002. These differences in rankings tell us that in terms of pollution control, Florida Power and Light Co. outperformed Pacific Gas and Electric Co. The median firm changes over time and is also different between the two models. Therefore, the ranking of the technical efficiency score changes every year as firms adjust their production technology, although the most efficient and the least efficient firms remained relatively stable in the ranking.

Table 1.12: Technical Efficiency Score of Most Efficient, Least Efficient and Median Firms

	Ignore Emissions			Consider Emissions		
Year	Most Eff.	Least Eff.	Median	Most Eff.	Least Eff.	Median
1988	0.917 (45)	0.368 (73)	0.786 (67)	0.893 (45)	0.380 (73)	0.778 (68)
1989	0.921 (45)	0.361 (73)	0.787 (67)	0.898 (45)	0.377 (73)	0.781 (68)
1990	0.925 (45)	0.354 (73)	0.788 (67)	0.904 (45)	0.375 (73)	0.784 (68)
1991	0.929 (45)	0.348 (73)	0.790 (8)	0.910 (45)	0.373 (73)	0.787 (68)
1992	0.933 (45)	0.341 (73)	0.791 (16)	0.915 (45)	0.371 (73)	0.791 (68)
1993	0.937 (45)	0.334 (73)	0.793 (16)	0.921 (45)	0.368 (73)	0.796 (8)
1994	0.941 (45)	0.328 (73)	0.794 (16)	0.927 (45)	0.366(73)	0.804 (8)
1995	0.945 (45)	0.322 (73)	0.795 (54)	0.933 (45)	0.364 (73)	0.811 (8)
1996	0.949 (45)	0.315 (73)	0.796(54)	0.939 (45)	0.362 (73)	0.817 (5)
1997	0.953 (45)	0.309 (73)	0.797 (54)	0.944 (45)	0.360 (73)	0.819 (16)
1998	0.957 (45)	0.304 (73)	0.801 (16)	0.950 (45)	0.358 (73)	0.823(5)
1999	0.962 (45)	0.298 (73)	0.800 (67/23)	0.956 (45)	0.355 (73)	0.824(16/5)
2000	0.966 (45)	0.292 (73)	0.804 (16)	0.962 (45)	0.353 (73)	0.824 (16)
2001	0.970 (45)	0.286 (73)	0.824 (5)	0.969 (45)	0.351 (73)	0.832 (71)
2002	0.974 (45)	0.430 (29)	0.824 (24/5)	0.975 (45)	0.419 (55)	0.834 (5/71)
2003	0.978 (45)	0.429 (29)	0.824 (5)	0.981 (45)	0.421 (55)	0.837(71)
2004	0.983 (45)	0.428 (29)	0.825 (5)	0.987 (45)	0.423 (55)	0.840(71)
2005	0.987 (45)	0.427 (29)	0.825 (5)	0.993(45)	0.426 (55)	0.838(59)

Note: firm rank order in parentheses.

For comparison purposes, I also apply the traditional input distance function approach, treating emissions as technology shifters. First, to use the translog functional form, I divide the input and output variables by their means, as opposed to the standardized values used in the directional distance function approach. Thus, the input and output variables are positive and unit-free. I estimate the following model and impose the restrictions in (1.31):

$$0 = D_i^t(ln\mathbf{x}_{it}, ln\mathbf{y}_{it}, ln\mathbf{b}_{it}) + f_i + \tau_t + vint_{it} + vint_{it}^2 + lnpstmq_{it} + \epsilon_{it}. \tag{1.34}$$

The results from this approach also show that efficiency change is small relative to technical change over time. PC measured by this method shows an aggregate level of negative growth over time. This is consistent with the finding in Atkinson and Dorfman (2005) for their sample period of 1980–1995. Using the input distance function to measure productivity and efficiency change may underestimate technical improvement because the reduction in bad outputs is not reflected in the change of input distances.

1.4.2 PC, EC, and TC with Consideration of Industry Structural Change

To further examine the reason for slow, overall productivity growth in the electric utility industry during my sample period, I consider the structural change that has taken place since the mid-1990s. As environmental policy became more stringent, some firms chose to shut down or sell off their steam electricity generation assets and become electricity distributors and wholesalers. In table (1.13), I compare the estimated directional distances of different firms. I employ the unbalanced panel data set of 78 firms and report the means and standard deviations of the estimated output directional distances for all firms. I then divide the firms into two groups: Group 1 comprises firms that produced continuously until 2005, Group 2 includes the firms that ceased steam electricity generation at some point during the sample period. After I normalize the fitted values of the directional distances, I compute the means and standard deviations for Group 1 firms (producers) and Group 2 firms (distributors or shutdowns). In this table, $\mathrm{DD_0T_0}$, or $\overrightarrow{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}, t)$, is the estimated directional distance of current-time-period production factors with the time variable evaluated at the current time period. $\mathrm{DD_0T_1}$, or $\overrightarrow{D}_o^{t+1}(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}, t+1)$, is the estimated distance of current-time-period production factors with the time variable evaluated at the future time period. Similarly, $\mathrm{DD_1T_0}$, or $\overrightarrow{D}_o^t(\mathbf{x}_{i,t+1}, \mathbf{y}_{i,t+1}, \mathbf{b}_{i,t+1}, t)$, is the estimated distance of the future-time-period production factors with the time variables evaluated at the current time period. Last, DD_1T_1, or $\overrightarrow{D}_o^{t+1}(\mathbf{x}_{i,t+1}, \mathbf{y}_{i,t+1}, \mathbf{b}_{i,t+1}, t+1)$, is the estimated distance of the future-time-period production factors with the time variables evaluated at the future time period. The results show that overall, Group 1 firms are more efficient than Group 2 firms since the estimated directional distances evaluated at both the current time period and the future time period for Group 1 are closer to 0 than Group 2 firms. A similar pattern emerges for the two groups during the period of 1988–1997 with the balanced panel data as well.

Table 1.13: Estimated Output Directional Distances

	all firms		group 1 firms		group 2 firms	
Estimated Distances	mean	std. dev	mean	std. dev	mean	std. dev
DD_0T_0	0.29847	0.051865	0.29778	0.047200	0.30027	0.062398
DD_0T_1	0.30655	0.052272	0.30575	0.047673	0.30863	0.062674
DD_1T_0	0.28969	0.052461	0.28939	0.047446	0.29048	0.063722
DD_1T_1	0.29777	0.052042	0.29736	0.046602	0.29884	0.064094

Next, to get a better estimation of the industry's productivity growth and efficiency change, I introduce a static binary variable, P (*produce*), which takes an value of 1 for the firms that produce throughout the 18 years and 0 for the firms that ceased their steam electricity generation within this time frame, and let P interact with all the input and output variables to allow for the differences between these two groups of firms. The estimated model for the directional distance function becomes

$$\begin{aligned}\overrightarrow{D}_o^t(\mathbf{x}_{it}, \mathbf{y}_{it}, \mathbf{b}_{it}; 0, 1, -1) \quad = \quad & \alpha_0 + \lambda P + \sum_{n=1}^{3} x_{n,it}(\alpha_n + \alpha_{P,n}P) \\ & + \sum_{g=1}^{2} y_{g,it}(\beta_g + \beta_{P,g}P) + \sum_{\omega=1}^{3} b_{\omega,it}(\phi_\omega + \phi_{P,\omega}P) \\ & + \frac{1}{2}\sum_{n=1}^{3}\sum_{n\prime=1}^{3} \alpha_{nn\prime} x_{n,it} x_{n\prime,it} + \frac{1}{2}\sum_{g=1}^{2}\sum_{g\prime=1}^{2} \beta_{gg\prime} y_{g,it} y_{g\prime,it} \\ & + \frac{1}{2}\sum_{\omega=1}^{3}\sum_{\omega\prime=1}^{3} \phi_{\omega\omega\prime} b_{\omega,it} b_{\omega\prime,it} + \sum_{g=1}^{2}\sum_{n=1}^{3} \gamma_{gn} y_{g,it} x_{n,it}\end{aligned}$$

$$+\sum_{\omega=1}^{3}\sum_{n=1}^{3}\delta_{\omega n}b_{\omega,it}x_{n,it}+\sum_{g=1}^{2}\sum_{\omega=1}^{3}\theta_{g\omega}y_{g.it}b_{\omega,it}. \tag{1.35}$$

The restrictions on the parameters need to be modified:

$$\begin{aligned}
\sum_{g=1}^{G}\beta_g-\sum_{\omega=1}^{B}\phi_\omega &= -1,\\
\sum_{g=1}^{2}\beta_{P,g}-\sum_{\omega=1}^{3}\phi_{P,\omega} &= 0,\\
\sum_{g=1}^{2}\beta_{gg\prime}-\sum_{\omega=1}^{3}\theta_{\omega g\prime} &= 0,\ \forall\ g,\\
\sum_{g=1}^{2}\gamma_{gn}-\sum_{\omega=1}^{3}\delta_{\omega n} &= 0,\ \forall\ n,\\
\sum_{g=1}^{2}\theta_{g\omega}-\sum_{\omega=1}^{3}\phi_{\omega\omega} &= 0,\ \forall\ \omega.
\end{aligned} \tag{1.36}$$

Table (1.14) shows the results from re-estimating the quadratic output directional distance function with a binary variable, P, included. The coefficient on P is -.231384 and is statistically significant. This means that firms that continuously produced are more technically efficient than the firms that chose to shut down or sell off their assets.

Table 1.14: Modified Output Quadratic Directional Distance Model (with Dummy, *Produce*)

Variable	Coefficient (t-stat)[3]
Inputs:	
Capital	.059525
	(5.49208)**
Labor	.491540E-02
	(.511380)
Energy	-.110723
	(-3.82517)**
Capital*Produce	-.011712
	(-.919196)

Variable	Coefficient (t-stat)
Labor*Produce	-.021775
	(-2.20553)**
Energy*Produce	.267565
	(8.03995)**
Capital^2	-.017591
	(-1.99116)**
Labor^2	-.100518E-02
	(-.403290)
Energy^2	-.091855
	(-2.38229)**
Capital*Labor	-.847395E-02
	(-1.39648)
Capital*Energy	.096284
	(6.10683)**
Labor*Energy	.029171
	(2.28335)**
Outputs:	
Residential	-.118122
	(-4.74449)**
Industrial and Commercial	-.593533
	(-17.1032)**
Residential*Produce	-.163941
	(-5.98237)**
Industrial Commercial*Produce	.081552
	(2.18932)**
Residential^2	.148177
	(7.21979)**
Industrial and Commercial^2	.115359

Variable	Coefficient (t-stat)
	(10.3729)**
Emissions:	
SO_2	.718857E-02
	(.456882)
CO_2	.356817
	(12.1594)**
NO_X	-.075661
	(-3.04637)**
SO_2*Produce	.064158
	(3.87632)**
CO_2*Produce	-.202346
	(-7.26282)**
NO_X*Produce	.055800
	(2.31481)**
${SO_2}^2$	-.018410
	(-2.87182)**
${CO_2}^2$	.284349
	(10.5386)**
${NO_X}^2$	-.570204E-2
	(-.981006)
Other Control Variables:	
Vintage	.351382E-02
	(3.22093)**
Vintage^2	-.867937E-04
	(-3.77576)**
Nonsteam	.060775
	(7.25170)**
Produce	-.231384

Variable	Coefficient (t-stat)
	(-8.53610)**

Note: Double asterisk indicates significance at the .05 level

1.5 Summary and Conclusions

As environmental issues are drawing attention worldwide, regulations on pollution are becoming more stringent. These changes are forcing the producers in many industries to adopt different technologies and engage in pollution abatement and environmental improvement. In the United States, a cap-and-trade system was established for SO_2 emissions in 1996 and for NO_X emissions in 1999. Although CO_2 emissions are not yet regulated in the U.S., Europe has recently adopted a CO_2 regulation scheme. The existing literature on this subject seldom examines years that include both pre- and post-regulation changes.

This chapter studied productivity and efficiency changes in the U.S. fossil fuel electric utility industry from 1988 to 2005. I applied the quadratic output directional distance function to measure the technical efficiency of this production technology, allowing for multiple inputs and multiple outputs, including three types of emissions: SO_2, NO_X, and CO_2. In keeping with many previous studies, I first estimated a model in which emissions were ignored. I then added the three types of emissions into the model and re-estimated the quadratic output directional distance function. I applied the index-number approach, which computes ratios of distances as Malmquist productivity indices, and a difference-in-log distances approach to measure productivity and efficiency change. The paper compares the different approaches and shows that Malmquist index numbers and the difference-in-log-distances models based on the directional distance function yield similar results. Over time, the industry's productivity grew gradually by about 0.8% every year with small fluctuations. Technical efficiency improvement was the main force behind productivity growth;

the catching-up effect, or EC, was fairly small. From the results of the difference-in-log-distances approach, I computed the average technical efficiency scores and found that, over time, Montana Dakota Utilities Co. was the most efficient firm and Texas Utilities Electric Co. was the least efficient firm in the sample. The TE score rankings changed every year as firms adjusted their production levels. I also estimated the technology with a translog input distance function model, which yielded declining efficiency and productivity change that is partially consistent with the findings of Atkinson and Dorfman (2005). The distance-function-based methods underestimated productivity growth by failing to credit the firms for the contraction of undesirable by-products.

Since the late 1990s, this industry has witnessed substantial structural change, with many firms shutting down or merging with other firms and ceasing their steam electricity generation. I distinguished firms that continuously produced from firms that stopped producing by introducing a binary variable and letting it interact with other input and output variables in the estimation of the directional distances. My results support the prediction that firms which stopped their steam electricity generation were less efficient. Therefore, as environmental regulations reshaped this industry, less efficient firms were forced out of production, and firms that were more efficient and productive survived environmental regulatory changes and kept growing. This partially answers the question of whether environmental regulations hurt or helped the U.S. fossil-fuel electric utility industry. Although environmental regulations shrank the size of the industry, they did not hurt the industry's growth in terms of productivity and efficiency.

Based on my empirical results, more studies can be done on this subject to further examine firms' decisions about whether to be either a producer or a distributor, a typical "make or buy" decision in industrial organization. Another possible extension of this paper could be to use regression discontinuity analyses. One such analysis could focus on the time period of 1995–2005 and apply a Sharp Regression Discontinuity design (SRD) (e.g., Imbens and Wooldridge, 2007; DiNardo and Lee, 2004) to examine if a cap-and-trade system for air pollution that affects firms' resource allocation in the short run would cause a discontinuous change in productivity in a lagged period and therefore affect the shutdown cutoff point. A regression discontinuity approach focuses on the firms with productivity or efficiency level at the margin between shutting down or staying in business and explains the effectiveness of environmental regulation changes. In addition, one can also focus on the deregulation or market restructuring of this industry since the late 1990s, and investigate the effects of restructuring on firm performance across different states. The methodology in this paper can be also applied to analyses in other industries such as the automobile industry, which is currently facing regulatory changes resulting from its negative externalities.

Chapter 2

Efficiency Implications of Competitive Restructuring

2.1 Introduction

The U.S. electric power industry had been a highly regulated industry until the late 1990s, with firms operating in the form of natural monopolies. In recent decades, as technology advances gradually changed the production characteristics, regulators and economists advocated the promotion of competition to reduce regional price disparity and inefficiency. A wave of deregulation policies that aimed to promote competition in the electricity retail market led to drastic changes in some states, including major mergers and acquisitions, and divesting activities. However, the outcomes vary across the states. Some states implemented deregulation, some stayed with their original structure, and some failed to achieve the intended goal of deregulation and suspended further deregulation a few years later.

There has been much debate and empirical studies on the various effects of deregulation in the electric utility industry by scholars and policy makers. One area of interest lies in examining the efficiency gains from deregulation, and the studies show mixed findings. Previous literatures have studied the efficiency and productivity change from deregulation in various industries, such as telecommunication, airline, and railroad. Kleit and Terrell (2001) examined the potential efficiency gains in electric power generation plants from deregulation. Using a Bayesian stochastic frontier model, they studied 78 steam plants whose production relied primarily on natural gas in the year 1996. Their results indicated that plants, on average, could reduce costs by up to 13% by eliminating production inefficiency. Goto and Tsutsui (2008) studied the impact of deregulation on technical efficiency change in electric utilities in their generation, transmission/distribution, and general administration functions. Applying the input distance function and stochastic frontier approach they examined technical efficiency change using annual data for 22 U.S. electric utilities firms from 1992-2000, and found that firms located in states that have enforced deregulation are less efficient. Furthermore, they showed that, although the efficiency trend was stable in the firms located in states with slower deregulation, efficiency improvements were observed for firms in deregulation-active states for the generation sector after 1997. Using data envelopment analysis (DEA) on 177 U.S. electric utilities from 1998 to 2001, Delmas and Tokat (2005) showed that deregulation had a negative impact on firms' productive efficiency.

One aspect that separates the electric utilities industry from many other industries that went through deregulation is that the production of steam electricity generation has negative environmental effects. Therefore, the firms face uncertainty not only from institutional changes but also from environmental regulatory changes. Many studies focused on the effect of deregulation on these environmental effects. Fowlie (2010) investigated the effect of economic regulation on the pollution permit market. She focused on NOx pollution control programs using a panel dataset of 702 coal-fired generating units within privately owned and publicly owned utilities in the U.S. between 2000 and 2004. Her study shows that deregulated plants in restructured electricity markets are less likely to adopt capital-intensive environmental compliance programs. In addition, she examined the factors that influence managers' choice among environmental compliance options, and concluded that heterogeneity in electricity market regulation leads to less-than-optimal compliance choices and a larger share of the permitted pollution being emitted in states where air quality problems tend to be more severe. Delmas, Russo, and Montes-Sancho (2007) found evidence that deregulation has stimulated environmental differentiation, as some firms increase their share of renewable generation and green power. However, this tendency toward environmental differentiation is lessened if firms depend relatively more on coal-fired generation or if they are relatively more efficient. Sanyal et al. (2007, 2009, 2013) conducted several studies of the effect of deregulation on innovation and R&D expenditures in the U.S. electric utilities industry.

Using R&D expenditure data from FERC Form-1 firm financial data or patent data, they showed that deregulation has a negative impact on firms' innovation quality and generality. Furthermore, although pollution abatement R&D may increase as a result of more stringent environmental policies, public-interest environmental research with social goals such as global warming research has declined as a result of deregulation.

For this chapter, I constructed a panel dataset of 377 fossil-fuel electricity-generating plants within the 78 investor-owned utilities for the sample period 1998 to 2005. The majority of the variables measuring production and emissions are derived from boiler level or combustion level data. The restructuring indicator is based on the location of the plants instead of the utilities, which better reflects the regulatory changes each power plant or electricity-generating unit faces. This chapter studies how deregulation affects power plants in terms of efficiency and productivity changes; in addition, after controlling for plant characteristics such as plant location, fuel quality, and vintage, I study whether deregulation affects the pollution level and the distribution of pollution among different states. Furthermore, the sample dataset at a more granular level allows me to compare changes in plant-level efficiency rankings, and examine the different effects of firms' various strategies in comply with restructuring and environmental regulations.

This chapter contributes to the previous literature in several aspects. First, to examine the efficiency impact of deregulation and address the conflicting empirical findings from previous studies, this paper has better data coverage which includes a majority of the investor-owned utilities at the generating-plant level and over a longer period following deregulation. Second, to study the environmental impact of deregulation, I examined three types of emissions, SO_2, NO_X, and CO_2. I also broke down the energy source into coal, petroleum, and gas as different fuel types have different level of pollutant contents. This allows me to control for the differentiation of fuel quality among different plants and any fuel-switching activities as part of their environmental compliance strategies. Previous studies mostly focused on only one or two types of emission and do not distinguish among fossil-fuel types as different emission sources.

2.2 Background

The U.S. electric power industry had been a highly regulated industry, where power generation was dominated by vertically integrated investor-owned utilities, until a substantial structural change began in the late 1990s. Historically, an industry characteristics meant that it was more efficient to operate in the form of natural monopoly. For example, with coal-fired power plants providing the major generating capacity, the cost of capital investment to expand capacity or to build a transmission system is very high. Therefore, a large centralized utility which has its own power-generating plants, transmission and distribution systems can achieve economies of scale and operate more efficiently than smaller firms can. In the electricity market, the industry allowed competition at the wholesale level as a result of the Public Utility Regulatory Policy Act of 1978 (PURPA).[1] Furthermore, the National Energy Policy Act of 1992 and state programs required utilities to meet additional generation demands through competitive bidding. However, the retail market remained dominated by natural monopolies that are subject to rate-of-return regulations.

Such industry structure created a large electricity price disparity in the retail market among utilities in different states. Prices to both residential electricity customers and large industrial electricity consumers were significantly higher in most states in the Northeast, as well as in California and Arizona. Table (2.1) shows the average retail price for the electric industry sector from 1995 to 2010. Overall, the average retail price of electricity was relatively stable in the 1990s; however, there was large price disparity across regions. In 1995, shortly before deregulation began across different states, the average retail price in Connecticut, New

[1] The Public Utility Regulatory Policies Act is part of the National Energy Act. It aims to promote greater use of domestic renewable energy. It requires the electric utilities to purchase their demand requirements from other sources that use renewable fuels when it is more efficient than generating the power by themselves.

Hampshire, New York and a few other states in the Northeast was over 10 cents per kilowatt hour, while other states, such as Indiana, Kentucky, and Washington, had an average price at only slightly over 4 cents per kilowatt hour.

Table 2.1: Total Electric Industry: Average Retail Price (Cents/kilowatthour) by State, by Year.

	1990	1995	2000	2005	2010
AK	9.48	10.17	10.08	11.72	14.76
AL	5.57	5.47	5.61	6.46	8.89
AR	6.70	6.27	5.77	6.30	7.28
AZ	7.75	7.62	7.25	7.79	9.69
CA	8.84	9.91	9.47	11.63	13.01
CO	5.89	6.12	5.88	7.64	9.15
CT	9.16	10.50	9.52	12.06	17.39
DC	5.94	7.12	7.52	9.18	13.35
DE	6.46	6.91	6.08	7.76	11.97
FL	7.04	7.01	6.91	8.76	10.58
GA	6.56	6.62	6.21	7.43	8.87
HI	9.02	11.29	14.03	18.33	25.12
IA	5.93	6.03	5.93	6.69	7.66
ID	3.80	4.09	4.17	5.12	6.54
IL	7.49	7.69	6.94	6.95	9.13
IN	5.36	5.24	5.18	5.88	7.67
KS	6.57	6.56	6.27	6.55	8.35
KY	4.48	4.07	4.18	5.01	6.73
LA	6.00	5.75	6.48	8.03	7.80
MA	8.85	10.12	9.49	12.18	14.26
MD	6.30	7.06	6.74	8.13	12.70
ME	7.65	9.49	9.69	10.57	12.84
MI	7.10	7.05	7.11	7.23	9.88

	1990	1995	2000	2005	2010
MN	5.33	5.58	5.87	6.61	8.41
MO	6.46	6.25	6.02	6.13	7.78
MS	6.11	5.98	5.85	7.54	8.59
MT	3.96	4.65	5.00	6.72	7.88
NC	6.38	6.58	6.48	7.19	8.67
ND	5.75	5.71	5.44	5.92	7.11
NE	5.57	5.40	5.31	5.87	7.52
NH	9.09	11.72	11.25	12.53	14.84
NJ	9.08	10.44	9.47	10.89	14.68
NM	7.10	6.77	6.58	7.51	8.40
NV	5.38	6.10	6.17	9.02	9.73
NY	9.37	11.06	11.38	13.95	16.41
OH	5.89	6.24	6.41	7.08	9.14
OK	5.48	5.57	5.88	6.85	7.59
OR	4.18	4.67	4.89	6.34	7.56
PA	7.65	7.93	7.65	8.27	10.31
RI	9.15	10.38	10.18	11.97	14.08
SC	5.59	5.69	5.62	6.72	8.49
SD	6.13	6.20	6.32	6.60	7.82
TN	5.31	5.21	5.58	6.31	8.61
TX	5.78	6.10	6.49	9.14	9.34
UT	5.46	5.30	4.84	5.92	6.94
VA	6.03	6.26	5.94	6.64	8.69
VT	8.28	9.46	10.27	10.95	13.24
WA	3.40	4.10	4.33	5.87	6.66
WI	5.37	5.36	5.71	7.48	9.78
WV	4.73	5.34	5.07	5.15	7.45
WY	4.21	4.32	4.34	5.16	6.20
US	**6.57**	**6.89**	**6.81**	**8.14**	**9.83**

Source: EIA-861.

To examine further price disparity across the nation, I compute the standard deviation of the average retail prices by the retail market segments, residential, commercial, and industrial for each year. Table (2.2) shows the annual trend from 1990 to 2005. Electricity sold to residential consumers has a greater discrepancy in average retail prices than to commercial and industrial uses. In addition, this price disparity has been increasing from 1990 and peaked in 1997. It then dropped slightly in the following three years until 2000. Since then it has been climbing again and the standard deviation in 2005 in the average retail prices was larger than the previous peak level in 1997.

Table 2.2: Average Retail Price Disparity: Standard Deviation by Year

Year	Residential	Commercial	Industrial	Total
1990	1.6687	1.4837	1.4286	1.5785
1991	1.8416	1.6332	1.5579	1.7172
1992	1.9442	1.6928	1.6232	1.8275
1993	2.1016	1.8106	1.6947	1.9349
1994	2.1355	1.8372	1.6694	1.9593
1995	2.2708	1.9088	1.7204	2.0507
1996	2.3414	1.9686	1.7335	2.0990
1997	2.4284	2.0316	1.7484	2.1562
1998	2.2500	1.8831	1.6178	1.9980
1999	2.1984	1.7921	1.5788	1.9325
2000	2.3085	2.0687	1.8005	2.1075
2001	2.3593	2.2826	1.8836	2.2119
2002	2.1670	2.0657	1.7751	2.0540
2003	2.2571	2.1263	1.8966	2.1642
2004	2.3696	2.1869	1.9868	2.2558
2005	2.7610	2.5851	2.5743	2.6399

In recent decades technological advances have made it possible to not only expand the electricity-generating capacity with much lower capital cost but also transmit power over longer distances. For example, aero-derivative gas turbines can generate electricity at the most efficient level at much lower capacity. With technological improvements and substantial price disparity, economists and regulators have promoted competition in this industry to lower prices, reduce inefficiency, and increase the variety of suppliers such as renewable energy electricity-generating plants. In the late 1990s, the Federal Energy Regulatory Commission (FERC) initiated regulatory reforms to move the electric power industry from a regulated monopolistic market towards a competitive market. Those states with higher prices had more instances of restructuring.

Table (2.3) shows the time line of the restructuring activities gathered by the Energy Information Administration (EIA) from state public utility commissions, state legislatures, and utility company web pages. The information was updated twice, on February 2003 and September 2010.

Table 2.3: U.S. Electric Industry Restructuring Activity

	Status Code[2]		Year of Deregulation by Sector		
State	By Sep 2010	By Feb 2003	Residential	Commercial and Industrial	Full Retail
Alabama	4	4			
Alaska	4	4			
Arizona[1]	3	1	1998	1998	2001
Arkansas[2]	3	2	2003	2003	2005

[2]Status code:
1 = Restructuring Active: Either enacted enabling legislation or issued a regulatory order to implement retail access.
2 = Restructuring Delayed
3 = Restructuring Suspended
4 = Restructuring Not Active

[1]Delayed in 2002, and suspended in 2007.
[2]Suspended in 2003.

	Status Code		Year of Deregulation by Sector		
State	By Sep 2010	By Feb 2003	Residential	Commercial and Industrial	Full Retail
California[3]	3	3	1998	1998	1998
Colorado	4	4			
Connecticut	1	1	2000	2000	2000
Delaware	1	1	2000	1999	2001
District of Columbia	1	1	2001	2001	2001
Florida	4	4			
Georgia	4	4			
Hawaii	4	4			
Idaho	4	4			
Illinois	1	1	2002	1999	2002
Indiana	4	4			
Iowa	4	4			
Kansas	4	4			
Kentucky	4	4			
Louisiana	4	4			
Maine	1	1	2000	2000	2000
Maryland	1	1	2000	2000	2002
Massachusetts	1	1	1998	1998	1998
Michigan	1	1	2002	2002	2002
Minnesota	4	4			
Mississippi	4	4			
Missouri	4	4			
Montana[4]	3	2	2004	2004	2004
Nebraska	4	4			
Nevada[5]	3	2		2002	2002
New Hampshire	1	1	2001	2001	2001
New Jersey	1	1	1999	1999	1999
New Mexico[6]	3	2	2007	2008	2008
New York	1	1	2001	2001	2001
North Carolina	4	4			
North Dakota	4	4			

[3]Suspended in 2001.
[4]Suspended in 2003.
[5]Suspended in 2003.
[6]Suspended in 2003.

State	Status Code By Sep 2010	Status Code By Feb 2003	Year of Deregulation by Sector: Residential	Commercial and Industrial	Full Retail
Ohio	1	1	2001	2001	2001
Oklahoma[7]	4	2			
Oregon[8]	1	1		2002	2002
Pennsylvania	1	1	1999	1999	2000
Rhode Island	1	1	1997	1997	1998
South Carolina	4	4			
South Dakota	4	4			
Tennessee	4	4			
Texas	1	1	2001	2001	2002
Utah	4	4			
Vermont	4	4			
Virginia[9]	3	1	2004	2004	2004
Washington	4	4			
West Virginia	4	4			
Wisconsin	4	4			
Wyoming	4	4			

According to the latest update in 2010, fifteen states and the District of Columbia are active in restructuring activities. The majority of these states are located in the Northeast Region and East North Central, except for Maryland, DC, Oregon and Texas. Meanwhile, seven states suspended their restructuring for various reasons. For example, in California, Assembly Bill 1890 (9/23/96) was enacted to restructure the California electric utility industry and implement retail direct access; that is, to allow consumers direct access to competitive suppliers of electric power. To reduce the market power of large utilities, the Bill required an independent system operator and legally separate power exchange in which all the buying and selling of electricity took place. It was scheduled to start as of March 31, 1998, for all consumers in investor-owned utilities' (IOU) service territories. As a result, the large

[7]Scheduled in 2002, then suspended.
[8]Suspended for residential sector.
[9]Suspended in 2007.

IOUs, such as Pacific Gas & Electric Co., Southern California Edison, and San Diego Gas & Electric Co., divested a large amount of generating capacity. However, the restructuring was not able to lower the electricity price because of the deficiency of generating capacity compared to high electricity demand. In the summer of 2000, San Francisco had rolling periods of blackouts and San Diego saw the retail price double. Restructuring activities in California were then suspended in 2001, since it failed to achieve the goal of lowering electricity prices. Comparing the deregulation time line with the average retail price in table (2.1), we see that the effectiveness of restructuring in reducing price disparity varies in different states.

In compliance with federal legislative and regulatory changes and to better position themselves in a competitive environment, there has been a wave of mergers and acquisitions and divestitures during restructuring. Appendix table (A.1) lists the major M&A or divesting activities in my data sample. Twenty eight out of seventy eight utilities had various restructuring activities during the sample period 1998 to 2005. The table shows that the majority of these activities were in states that enacted deregulation legislation, such as Illinois, Maryland, Pennsylvania and Texas. In some cases, data are no longer available at the plant or the firm level after the changes.

2.3 Data Description

2.3.1 Data source and sample period

Built on the study of the seventy eight investor-owned utilities in the previous chapter, this chapter constructs a panel dataset at a more granular level to examine all the electricity-generating plants for the same set of utility firms. The data are mainly sourced from form EIA-767 Steam Electric Plant Operation and Design Report, EIA-920/906, FERC Form-1, FERC-423, and IECM model estimation.

The sample period covers years 1998-2005 because of data inconsistency for several variables collected from different sources between 1988-1997 and 1998-2005. In addition, this time window covers the main period of industry restructuring activities, and it starts a few years after the passage of Title IV of the 1990 Clean Air Act on SO_2 emissions. Therefore, it allows me to focus on the effect of industry deregulation and restructuring.

2.3.2 Variable derivation and methodologies

The dataset consists of variables measuring input, output, emission, capacity, emission control cost, plant location, and industry restructuring indicators at the plant level.

Production Inputs

Similar to my previous study, the input variables contain information on fuel consumption, capital expenditure, and labor expenditure. Fuel consumption is broken down to the consumption of coal, natural gas, and petroleum, both in physical units and heat content (BTU). Depending on the geographic region for the source of the fuels, the quality of the fuels in different plants may vary significantly. From the heat contents and the physical units of different fuel types, I compare the fuel quality across the plants over time. Furthermore, I collected data on sulfur contents for the three types of fuels in each plant. The previous chapter only studies the total fuel consumption at each utility, and the additional variables in this chapter allow me to study production decisions such as fuel switching. For example, plants that consume natural gas only will not have sulfur dioxide emissions, and therefore are less sensitive to environmental regulatory changes regarding sulfur dioxide. However, plants that rely heavily on coal consumption generate all three types of emissions, CO_2, SO_2, and NO_x.

For the capital input, I collected data on maximum generator nameplate rating, and then aggregated the generator-level data to obtain plant-level total capacity. Using plant capacity as the weight, I derived the plant-level expenditure on capital from the utility-level dataset. Finally, for the labor input, expenditure of labor, number of employers, and price of labor are calculated from utility-level data weighted by plant net electricity generation.

Production Output and Emissions

Output variables include good and bad outputs, that is, the quantity of steam electricity net generation, in kWh, and the three types of emissions, CO_2, SO_2, and NO_x, in tons. Quantity of electricity generation is collected directly from EIA-767, Schedule 5 Generator Information. The annual total generation is the sum of reported monthly net electrical generation, which is the total amount of electric energy generated, measured at the generator terminals, minus the total electric energy consumed at the generating station (e.g., pumps, fans, and ancillary consumption) for the time period indicated. The bad outputs of the three types of emissions are calculated from boiler and generator level data on fuel consumption, fuel type, sulfur content, emission factor, and emission control equipment. The methodology of computing emissions is consistent with the first chapter, which is described in detail in the Appendix, equations (A.1), (A.2), and (A.3).

Costs and Expenditures

Capital expenditure on emission control is an important factor in firms' production decisions, especially when they are facing changing environmental regulations. The cost of emission control depends mainly on fuel type, boiler type, and control equipment. However, data on capital expenditure for emission control are often challenging to obtain. In my study, I examined three alternative methods.

The first method uses data collected directly from EIA forms. Form EIA-767 reports data on expenditures on emission control. In Schedule 3. Plant Information, Part B reports financial information regarding pollution control in three categories: operation and maintenance (O&M) expenditures, capital expenditures on new structures and equipment, and byproduct sales revenue.

O&M expenditures consist of costs for both collection and disposal of the byproducts either through air emissions or water pollution, among which flue gas desulfurization (FGD) is one of the important, and refers to the process of removing sulfur dioxide. Expenditures on

FGD cover all material and labor costs, including equipment operation and maintenance costs associated with the collection and disposal of the sulfur byproduct. O&M expenditures also cover other pollution abatement expenses not allocated to one particular expenditure (e.g., expenditures to operate an environmental protection office or lab). It also includes expenses for conducting environmental studies for expansion or reduction of operations, and excludes all expenses for health, safety, employee comfort (OSHA), environmental aesthetics, research and development, taxes, fines, permits, legal fees, Superfund taxes, and contributions.

Capital expenditures for new structures and equipment, excluding land and interest expense, include all pollution abatement capital expenditures for new structures and/or equipment made during the reporting year regardless of the date they became operational. Air pollution abatement includes new structures and/or equipment purchased to reduce, monitor, or eliminate airborne pollutants, including particulate matter (dust, smoke, fly ash, dirt, etc.), sulfur dioxides, nitrogen oxides, carbon monoxide, hydrocarbons, odors, and other pollutants. Examples of air pollution abatement structures/equipment include flue gas particulate collectors, flue gas desulfurization units, continuous emissions monitoring equipment (CEMs), and nitrogen oxide control devices. Other pollution abatement includes amortizable expenses and purchases of new structures and/or equipment when such purchases are not allocated to a particular unit or item, and excludes all equipment purchased for aesthetic purposes. Examples include charges for the purchase of facilities to control hazardous waste, radiation, and noise pollution.

Byproduct sales revenue offsets the expenditures from the first two items, and one can compute the final net cost by subtracting byproduct sales revenue from the sum of O&M expenditures and new construction capital expenditures.

For nitrogen oxide control, Form EIA-767 Schedule 4 Boiler Information, Part D. Nitrogen Oxide Emission Controls collects information including nitrogen oxide control operation status, and nitrogen oxide control process. Schedule 8 Flue Gas Desulfurization Unit Information collects information on flue gas desulfurization (FGD) unit operation status, unit type, sorbent type, and removal efficiency.

The second approach is from IECM model estimation.[3] Chon (2011) applies the IECM model to estimate expenditures on emission control, which include capital expenditure on SO_2 control and capital expenditure on NO_x combustion and post-combustion. After feeding in information on fuel inputs, generating units, and combustion type, along with other variables on plant characteristics from a given year, the IECM model generates a time series of estimated capital expenditures on emission control.

However, after evaluating the capital expenditure data from both methods, I found that the data quality is questionable. The cost expenditures from the two sources are often inconsistent. On the EIA forms, many firms did not fully disclose their emission control expenditure. For the IECM model, the plant level data have a large portion of missing values due to limitations on the availability of the input variables that the model requires, and possible limitations of the IECM model itself. Many of the missing values or zero cost records are not reasonable given the plants' fuel consumption or electricity output and emission levels.

This study uses the third method to measure the capital expenditure on emission control. I use the utility level data of total capital expenditure, derived from FERC Form-1 financial statement data, and derive the plant level total capital expenditure weighted by plant capacity. The capital expenditure on emission controls is then implicitly modeled as it is included as part of the total capital expenditure. Although not ideal, it is the best solution given the data availability and data quality constraints.

Restructuring Indicator

Based on the state restructuring status summarized in Table (2.3), I constructed a dummy variable to indicate the changing status for each plant in my sample. The restructuring

[3] The Integrated Environmental Control Model (IECM) is developed by Carnegie Mellon University, Department of Engineering and Public Policy. It is available at http://www.cmu.edu/epp/iecm/.

dummy takes on a value of 1 when restructuring is active, and 0 when restructuring is either not active or suspended. The following examples in Table (2.4) illustrate the definition of this variable.

Table 2.4: Example of Restructuring Dummy

Year	Utility Code	Utility Name	Utility State	Plant Code	Plant Name	Plant State	Restr. Dum.
1998	195	Alabama Power Co	AL	3	Barry	AL	0
1999	195	Alabama Power Co	AL	3	Barry	AL	0
2000	195	Alabama Power Co	AL	3	Barry	AL	0
2001	195	Alabama Power Co	AL	3	Barry	AL	0
2002	195	Alabama Power Co	AL	3	Barry	AL	0
2003	195	Alabama Power Co	AL	3	Barry	AL	0
2004	195	Alabama Power Co	AL	3	Barry	AL	0
2005	195	Alabama Power Co	AL	3	Barry	AL	0
...							
1998	733	Appalachian Power Co	VA	3775	Clinch River	VA	0
1999	733	Appalachian Power Co	VA	3775	Clinch River	VA	0
2000	733	Appalachian Power Co	VA	3775	Clinch River	VA	0
2001	733	Appalachian Power Co	VA	3775	Clinch River	VA	0
2002	733	Appalachian Power Co	OH	3775	Clinch River	VA	0
2003	733	Appalachian Power Co	OH	3775	Clinch River	VA	0
2004	733	Appalachian Power Co	OH	3775	Clinch River	VA	1
2005	733	Appalachian Power Co	OH	3775	Clinch River	VA	1
...							
1998	803	Arizona Public Service Co	AZ	113	Cholla	AZ	1
1999	803	Arizona Public Service Co	AZ	113	Cholla	AZ	1
2000	803	Arizona Public Service Co	AZ	113	Cholla	AZ	1
2001	803	Arizona Public Service Co	AZ	113	Cholla	AZ	1
2002	803	Arizona Public Service Co	AZ	113	Cholla	AZ	0
2003	803	Arizona Public Service Co	AZ	113	Cholla	AZ	0
2004	803	Arizona Public Service Co	AZ	113	Cholla	AZ	0
2005	803	Arizona Public Service Co	AZ	113	Cholla	AZ	0
...							

The first example is Barry, a plant owned by the Alabama Power Co. Because Alabama did not have restructuring activities, the dummy variable takes on a value of 0 for the years 1998 to 2005. The second plant, Clinch River, owned by the Appalachian Power Co., is located in Virginia. Appalachian Power is a subsidiary of American Electric Power (AEP). Even though AEP has its headquarters in Ohio, the restructuring dummy is defined using plant location as it reflects the legislative and regulatory status the plant is actually in compliance with. Therefore, the dummy takes on a value of 0 from 1998 to 2003, and changes to 1 beginning in 2004 when Virginia plants were subject to restructuring. The third example is Cholla, a plant of Arizona Public Service Co., also located in Arizona. Arizona started restructuring in 1998, but it was delayed and suspended later. Therefore, the dummy variable takes on a value of 1 for the years 1998-2001, and then changes to 0 since 2002.

2.3.3 Summary statistics

Table (2.5) shows the mean, standard deviation, and description for all the variables in this study. The sample contains a total of 74 firms and 377 unique plants.

Table 2.5: Summary Statistics of Model Variables

Variable	Mean	Std Dev	Description
co2emission	4,340,388	5,119,808	CO2 emission (tons)
coal_heatcontent	36,450	48,590	Annual fuel consumption in heat content - coal (billion BTU)
coal_sulfurcontent	17	31	Sulfur content from coal (thousand short tons)
firmid	39	23	74 firms
gas_heatcontent	4,280	10,582	Annual fuel consumption in heat content - Gas (billion BTU)
nameplate_rating	864	746	Maximum generator nameplate rating (megawatts)
noxemission	11,596	16,288	NOx emission (tons)

Variable	Mean	Std Dev	Description
petroleum_heatcontent	1,612	6,415	Annual fuel consumption in heat content - Petroleum (billion BTU)
petroleum_sulfurcontent	3	13	Sulfur content from petroleum (thousand barrels)
plant_exp_fuel	6,987	7,764	Expenditure on fuel, derived from utility level data, weighted by total generation
plant_exp_labor	1,006	1,245	Expenditure on labor, derived from utility level data, weighted by nameplate_rating (capacity)
plant_exp_capital	1,996	2,065	Expenditure on capital expenditure, derived from utility level data, weighted by nameplate_rating (capacity)
plant_empl	799	1,294	Number of total employees (full-time + 1/2 part-time employees)
plant_ftempl	801	1,285	Number of full-time employees, derived from utility level data, weighted by nameplate_rating (capacity)
plant_ptemp	22	57	Number of part-time employees, derived from utility level data, weighted by nameplate_rating (capacity)
plantid	191	111	377 plants
quality_coal_heat	10,860	1,862	Fuel quality of coal (BTU per pound)
quality_coal_sulfur	0.0103	0.0078	Fuel quality of coal (sulfur by weight)
quality_gas_heat	1,129	1,138	Fuel quality of gas (BTU per cubic foot)

Variable	Mean	Std Dev	Description
quality_petro_heat	141,276	6,669	Fuel quality of petroleum (BTU per gallon)
quality_petro_sulfur	0.0043	0.0045	Fuel quality of petroleum (sulfur by weight)
restruct_dummy_pl	0.2029	0.4023	Restructuring flag based on the state of the utility
restruct_dummy_ut	0.2708	0.4445	Restructuring flag based on the state of the plant
so2emission	19,678	29,692	SO2 emission (tons)
tot_fuel	42,342	46,319	Annual fuel consumption in heat content - Total (billion BTU)
total_generation	4,162,136	4,675,638	Total net electricity generation - Annual (megawatt hours)
totcoal	1,784	2,506	Annual coal consumption - Total (thousand short tons)
totgas	4,182	10,302	Annual gas consumption - Total (million cubic feet)
totpetro	255	1,009	Annual petroleum consumption - Total (thousand barrels)
utility_price_labor	49,439	13,614	Price of labor at the utility level
year	2,001	2	Year (1998- 2005)

Table (2.6) summarizes the trend of output and emissions of the fossil-fuel steam-electricity generation plants from 1998 to 2005.[4] Figure (2.1), (2.2), and (2.3) summarize table Table (2.6). The total number of utilities I follow in this study decreases from 73 in year 1998 to only 54 in 2005. Similarly, the number of the steam electricity generating plants also drops from 352 to 251 during the sample period, a decrease of roughly 30%. Total

[4]Data summary in this table and the following tables, (2.7), (2.8), and (2.9), is computed after excluding the observations that contain missing value on either fuel consumption or total net generation.

capacity and net generation also declined as the sample size shrank and we see the biggest drop between 1999 to 2001. The last three columns show the trend of emissions of CO_2, NO_X, and SO_2. Emission levels go down as industry capacity and output level decreases.

Table 2.6: Trend of Capacity, Net Generation, and Emissions

Year	Num. of Firms	Num. of Plants	Capacity[a]	Generation[b]	CO_2	NO_X	SO_2[c]
1998	73	352	313	1,422,362	1,512,241	5,517	7,599
1999	68	326	284	1,330,003	1,402,311	5,095	6,686
2000	58	284	249	1,241,399	1,325,452	4,845	5,515
2001	54	276	230	1,102,899	1,128,760	2,440	5,018
2002	53	265	223	1,083,360	1,108,228	1,899	4,831
2003	53	258	222	1,085,178	1,087,099	1,859	4,771
2004	54	255	218	1,078,206	1,122,448	1,962	4,944
2005	54	251	219	1,092,157	1,153,119	2,671	5,245

[a] Maximum generator nameplate rating or capacity, reported in 1,000 magawatts.

[b] Total net electricity generation, reported in 1,000 megawatthours.

[c] Emissions of SO_2, CO_2, and NO_X are reported in 1,000 tons.

Fuel consumption is a key input into the production of electricity. Table (2.7) shows the yearly trend of the average quality of the three major fuel types, coal, gas, and petroleum, weighted by the quantity of fuel consumption. Fuel quality is measured by heat content and sulfur content. Between 1998 and 2005, overall fuel quality stays fairly stable. The heat contents for all three fuel types remain very stable, except for the last two years, when the heat contents of coal and petroleum exhibited a slight decrease, due partly to the change in sample size as more plants dropped out of the sample. In terms of sulfur content, petroleum contains more sulfur than coal, while natural gas contains no sulfur. Figure (2.4) summarizes table (2.7) on sulfur content by fuel types.

Figure 2.1: Total Electricity Generation Capacity of Power Plants, 1998-2005

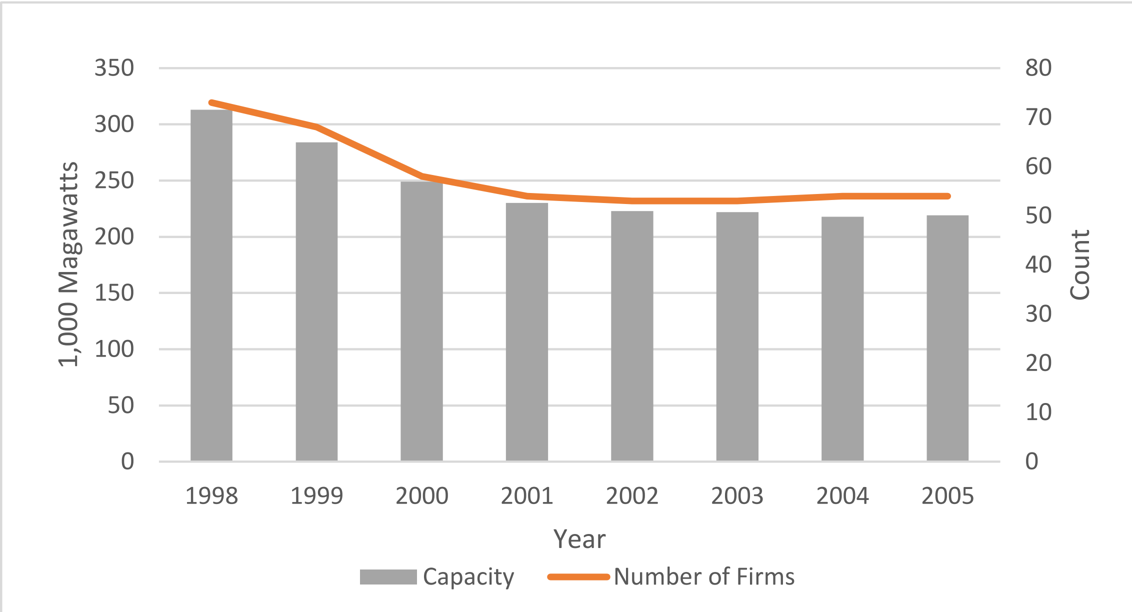


Figure 2.2: Trend of Total Electricity Generation of Power Plants, 1998-2005

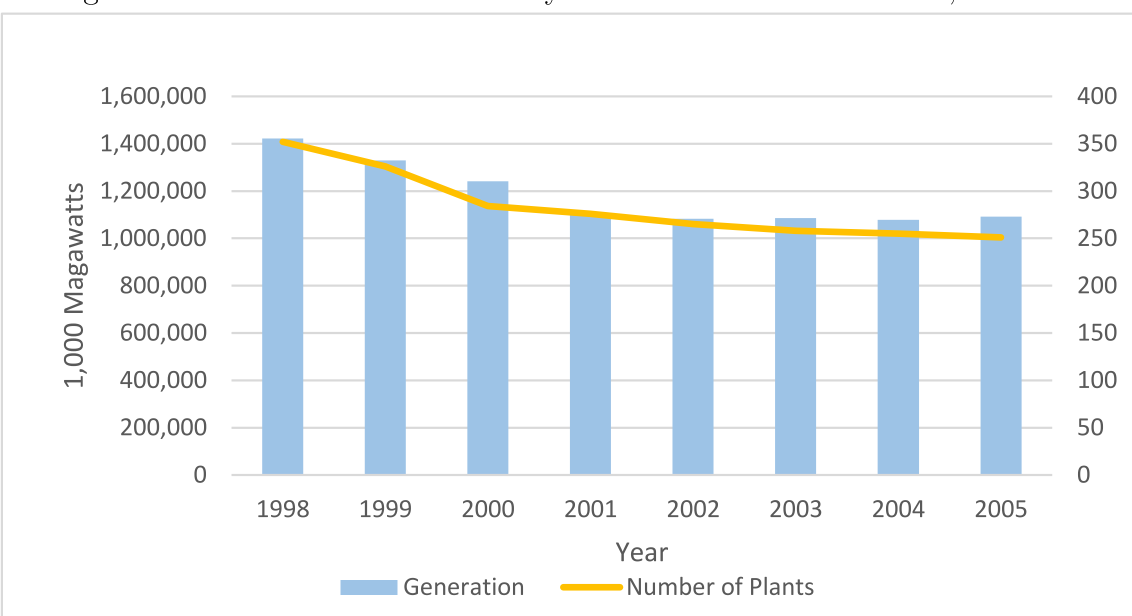


Figure 2.3: Trend of Total Emissions of Power Plants, 1998-2005

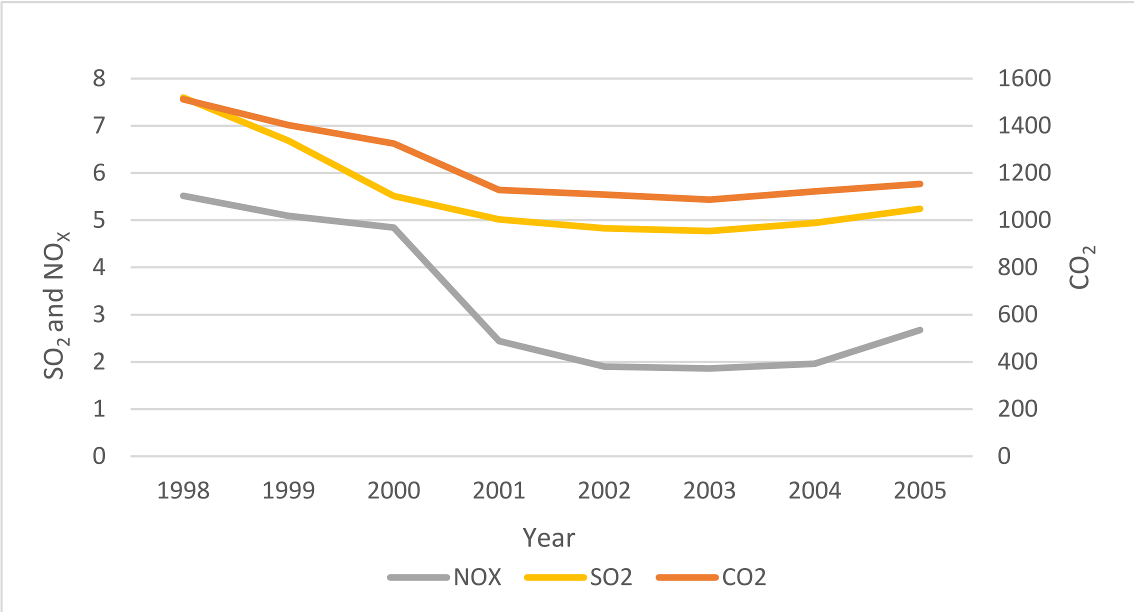
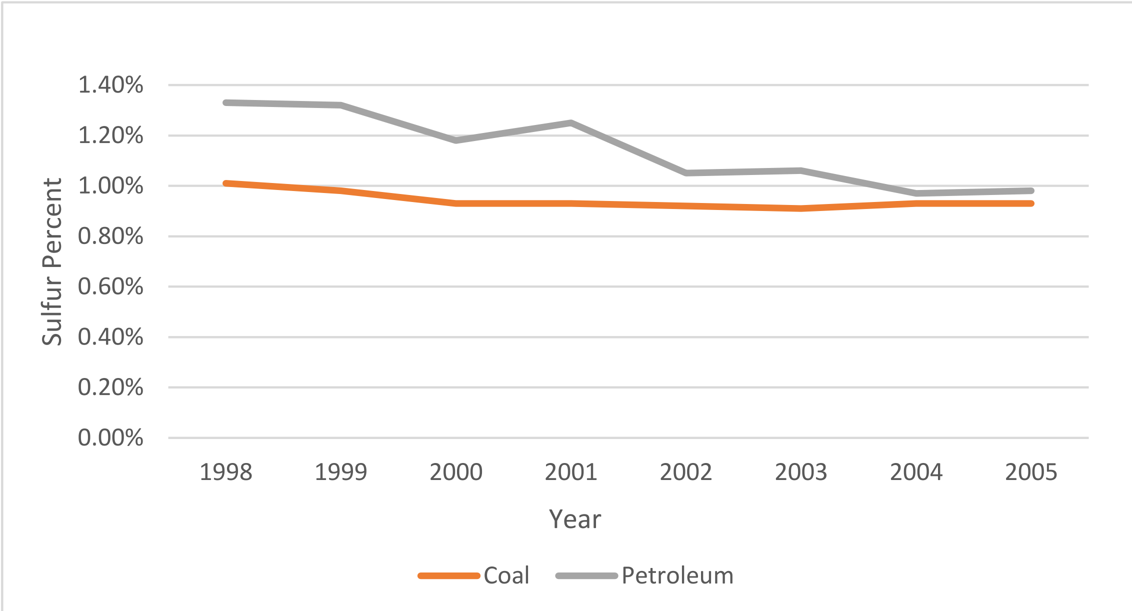


Table 2.7: Average Quality of Fossil-Fuel Consumption

			Coal		Petroleum		Gas
Year	Num. of Firms	Num. of Plants	Avg Btu/ Pound	Avg Sulfur Percent	Avg Btu/ Gallon	Avg Sulfur Percent	Avg Btu/ Cubic Foot
1998	73	352	10,244	1.01%	150,643	1.33%	1,024
1999	68	326	10,283	0.98%	150,656	1.32%	1,021
2000	58	284	10,206	0.93%	150,728	1.18%	1,025
2001	54	276	10,213	0.93%	151,025	1.25%	1,022
2002	53	265	10,264	0.92%	152,062	1.05%	1,021
2003	53	258	10,253	0.91%	152,072	1.06%	1,028
2004	54	255	10,141	0.93%	145,710	0.97%	1,026
2005	54	251	10,122	0.93%	151,975	0.98%	1,026

Due to the distance and cost constraints of electricity transmission, as well as the high fixed cost of building electricity generating capacity, power plants are usually immobile.

Figure 2.4: Comparison of Sulfur Content by Fuel Types



Depending on the plant location, the type of fuel inputs often varies across plants. The following two tables show the regional variation of fuel quality.

Table (2.8) shows the yearly trend of average fuel quality by nine census regions. Among these regions, the South Atlantic region has the largest number of fossil-fuel power plants, followed by West South Central and East South Central. The Pacific region, which includes California, Washington, Alaska, Oregon, and Hawaii, has the fewest number of fossil-fuel power plants, especially in the later years. The restructuring and divesting activities in California are the main reason for this. California also relies on other fuel-generating technology such as nuclear power plants.

For coal, the average heat contents vary from 7000 BTU/pound in West South Central to around 13,000 BTU/pound in the New England and Mid Atlantic regions. The average sulfur content of coal also varies substantially among regions. West North Central has the cleanest coal, with a sulfur content of around 0.45%. In the Mid Atlantic, the average sulfur content in coal is over 2%, and the South Atlantic has higher-quality coal, with high heat content and relatively lower sulfur content. As for the quality of natural gas, there are no regional differences in terms of average heat content. For petroleum, although heat contents are similar among regions, there is a significant difference in the sulfur content. The Mountain region has the cleanest petroleum and South Atlantic, West North Central, and New England have high-sulfur petroleum.

Table 2.8: Average Fuel Quality by Region

			Coal		Gas	Petroleum	
Year	Num. of Utilities	Num. of Plants	Avg Btu/ Pound	Avg Sulfur Percent	Avg Btu/ Cubic Foot	Avg Btu/ Gallon	Avg Sulfur Percent
East North Central							
1998	18	68	10,529	1.34%	1,018	142,296	0.43%
1999	16	56	10,738	1.37%	1,015	140,224	0.33%
2000	15	49	10,714	1.39%	1,013	140,145	0.40%
2001	15	51	10,629	1.36%	901	140,307	0.40%
2002	15	50	10,737	1.31%	899	142,993	0.57%
2003	14	48	10,751	1.37%	1,033	141,098	0.48%
2004	14	46	10,656	1.42%	1,025	141,051	0.42%
2005	14	46	10,651	1.37%	1,011	141,628	0.44%
East South Central							
1998	6	22	11,390	1.40%	1,030	148,801	2.29%
1999	6	22	11,090	1.35%	1,020	147,800	2.35%
2000	6	22	11,086	1.33%	1,020	142,462	2.57%
2001	6	22	11,047	1.30%	1,025	150,851	2.16%
2002	6	22	11,038	1.27%	1,030	140,105	0.40%
2003	7	25	11,043	1.25%	1,031	153,868	0.08%
2004	7	25	10,992	1.26%	921	152,587	0.25%
2005	7	25	10,865	1.26%	965	150,220	0.57%
Mid Atlantic							
1998	10	32	12,702	1.81%	1,037	150,424	0.81%
1999	10	26	12,826	1.82%	1,026	149,914	0.89%
2000	5	11	12,958	1.70%	1,025	150,463	0.77%
2001	3	5	12,835	2.07%	1,033	148,783	0.49%

Year	Num. of Utilities	Num. of Plants	Coal Avg Btu/ Pound	Coal Avg Sulfur Percent	Gas Avg Btu/ Cubic Foot	Petroleum Avg Btu/ Gallon	Petroleum Avg Sulfur Percent
2002	3	5	13,030	2.07%	1,031	148,613	0.53%
2003	3	5	13,047	2.00%	1,037	147,654	0.47%
2004	4	6	9,658	2.24%	1,034	147,933	0.36%
2005	4	5	7,856	2.43%	1,036	149,089	0.39%
Mountain							
1998	7	29	9,547	0.60%	1,012	138,627	0.14%
1999	6	27	9,786	0.55%	1,013	137,641	0.10%
2000	6	27	9,878	0.56%	1,021	140,384	0.30%
2001	6	28	9,838	0.57%	1,024	145,678	0.45%
2002	7	29	9,804	0.56%	1,016	138,438	0.08%
2003	7	29	9,815	0.56%	1,013	140,661	0.22%
2004	7	29	9,803	0.56%	1,014	138,505	0.06%
2005	7	29	9,835	0.57%	1,013	141,313	0.67%
New England							
1998	3	7	12,992	1.16%	1,028	151,410	1.23%
1999	1	3	13,077	1.39%	1,011	150,751	1.58%
2000	1	3	12,972	1.39%	1,066	151,845	1.65%
2001	1	3	13,003	1.41%	1,075	153,095	0.96%
2002	1	3	13,051	1.15%	1,050	152,167	1.29%
2003	1	3	13,150	1.06%		151,864	1.56%
2004	1	3	13,066	1.08%		152,016	1.43%
2005	1	3	12,821	1.19%		154,277	1.10%
Pacific							
1998	4	16	7,925	0.60%	1,023	143,805	0.36%
1999	4	11	7,928	0.73%	1,015	140,006	0.05%
2000	1	2			1,018	145,870	1.27%
2001	1	2			1,019	145,686	1.01%
2002	1	2			1,017	148,980	1.00%
2003	1	2			1,020	146,296	0.78%
2004	1	2			1,019		0.00%
2005	1	2			1,023		0.00%
South Atlantic							
1998	15	79	12,193	1.05%	1,007	151,173	1.39%
1999	15	79	12,215	1.05%	1,010	151,458	1.35%

			Coal		Gas	Petroleum	
Year	Num. of Utilities	Num. of Plants	Avg Btu/ Pound	Avg Sulfur Percent	Avg Btu/ Cubic Foot	Avg Btu/ Gallon	Avg Sulfur Percent
2000	12	68	12,186	0.96%	1,004	152,238	1.17%
2001	11	69	12,084	1.00%	1,004	151,654	1.21%
2002	11	66	12,080	0.97%	1,003	152,680	1.08%
2003	11	67	12,079	0.98%	1,003	152,671	1.13%
2004	11	66	11,806	0.97%	1,002	144,181	1.04%
2005	11	66	11,748	0.97%	1,004	152,700	1.03%
West North Central							
1998	6	23	8,864	0.46%	1,003	138,084	0.21%
1999	6	23	8,842	0.46%	1,020	147,542	0.91%
2000	6	23	8,863	0.43%	1,016	150,206	1.09%
2001	6	24	8,744	0.40%	1,020	149,650	1.36%
2002	5	18	8,693	0.48%	1,011	152,843	1.32%
2003	5	18	8,698	0.44%	1,026	154,811	1.31%
2004	5	18	8,652	0.45%	1,017	154,756	1.59%
2005	5	18	8,642	0.40%	1,013	154,960	1.58%
West South Central							
1998	11	76	7,639	0.64%	1,026	151,231	1.20%
1999	11	79	7,606	0.56%	1,023	147,890	0.94%
2000	11	79	7,715	0.54%	1,027	143,591	0.51%
2001	10	72	7,825	0.57%	1,027	148,143	0.65%
2002	10	70	7,843	0.58%	1,028	140,036	0.39%
2003	10	61	7,848	0.49%	1,031	147,190	0.68%
2004	10	60	7,858	0.51%	1,033	149,435	0.89%
2005	10	57	7,833	0.53%	1,034	148,639	0.69%

Table (2.9) summarizes the average fuel quality by state over the entire period 1998 to 2005. Texas has over 300 power plants and a high quality of the fuel input, especially petroleum, whose sulfur content is very low and heat content is high. Like table (2.8), the comparison shows large regional differences in the fuel quality of coal and petroleum.

Table 2.9: Fossil Fuel Quality by State, 1998-2005

		Coal		Gas	Petroleum	
Plant State	Num. of Plants	Coal Avg Btu / Pound	Avg Sulfur Percent	Gas Avg Btu / Cubic Foot	Petroleum Avg Btu / Gallon	Avg Sulfur Percent
East North Central						
IL	28	9,596	0.96%	1,019	145,110	0.48%
IN	115	10,492	1.50%	1,058	137,280	0.31%
MI	75	10,068	0.58%	928	144,502	0.59%
OH	130	11,767	1.98%	1,027	137,842	0.27%
WI	66	9,043	0.37%	1,009	134,286	0.23%
East South Central						
AL	57	10,668	0.71%	885	139,589	0.34%
KY	64	11,659	2.38%	1,025	138,969	0.34%
MS	64	11,094	0.66%	1,026	149,670	1.78%
Mid Atlantic						
NJ	26	12,780	1.54%	1,037	148,343	0.77%
NY	38	13,065	1.68%	1,032	150,027	0.88%
PA	31	11,951	2.04%	1,031	150,501	0.63%
Mountain						
AZ	37	9,805	0.49%	1,018	143,976	0.72%
CO	72	9,659	0.38%	994	143,805	0.72%
MT	6	8,381	0.71%	1,066	140,999	0.50%
NM	40	9,185	0.77%	1,012	135,704	0.10%
NV	8	12,280	0.49%	1,027		0.00%
UT	32	11,607	0.48%	1,051	139,999	0.05%
WY	32	9,002	0.57%	1,050	140,000	0.05%
New England						
CT	2	13,123	0.53%	1,028	151,878	0.99%
ME	2				151,063	1.28%
NH	24	13,007	1.25%	1,055	151,969	1.45%
Pacific						
CA	37			1,020	145,716	1.01%
WA	2	7,926	0.66%		139,997	0.05%

Plant State	Num. of Plants	Coal Coal Avg Btu / Pound	 Avg Sulfur Percent	Gas Gas Avg Btu / Cubic Foot	Petroleum Petroleum Avg Btu / Gallon	 Avg Sulfur Percent
South Atlantic						
DC	2				143,400	0.82%
DE	5	12,734	1.00%	1,037	149,022	0.69%
FL	150	11,907	1.43%	1,002	151,361	1.22%
GA	83	11,440	0.80%	1,029	145,545	1.59%
MD	19	12,918	1.28%	1,042	150,835	1.01%
NC	112	12,341	0.86%	1,038	139,201	0.23%
SC	61	12,513	1.16%	1,031	138,114	0.13%
VA	76	12,597	1.02%	1,052	150,985	1.09%
WV	52	12,141	1.08%		139,080	0.30%
West North Central						
IA	8	9,356	0.50%	1,016	139,998	0.43%
KS	24	8,628	0.69%	1,014	154,767	1.50%
MN	73	8,729	0.47%	1,012	138,934	0.24%
MO	56	8,782	0.36%	1,017	137,474	0.34%
ND	4	7,321	0.72%			0.00%
West South Central						
AR	56	8,615	0.28%	1,018	139,044	0.28%
LA	120	7,690	0.68%	1,033	150,936	0.92%
OK	40	8,745	0.26%	1,037	145,313	0.42%
TX	338	7,416	0.65%	1,024	141,072	0.32%

2.4 Econometric Models

2.4.1 Directional Distance Function

To model firm efficiency, I define the directional distance function as $\overrightarrow{D}_\tau$ ($\mathbf{x}$, $\tilde{\mathbf{x}}$, $\mathbf{y}$, $\tilde{\mathbf{y}}$) with a direction vector (-$\mathbf{g}_x$, -$\mathbf{g}_{\tilde{x}}$, $\mathbf{g}_y$, -$\mathbf{g}_{\tilde{y}}$), where vectors $\mathbf{x}$, $\tilde{\mathbf{x}}$, $\mathbf{y}$, and $\tilde{\mathbf{y}}$ denote good inputs, bad inputs, good outputs, and bad outputs, respectively. This is a general form of the output-oriented directional distance function discussed in the previous chapter, where the direction vector takes on the value ($\mathbf{0}$, $\mathbf{0}$, $\mathbf{g}_y$, -$\mathbf{g}_{\tilde{y}}$) when deriving the translation property. The function to be estimated is:

$$\begin{aligned}
0 &= \overrightarrow{D}_{\tau}^{t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}; -g_x, -g_{\tilde{x}}, g_y, -g_{\tilde{y}}) + \epsilon_{it} \\
&= \alpha_0 + \sum_{m=1}^{M} \beta_m x_{m,it} + \sum_{n=1}^{N} \beta_n \tilde{x}_{n,it} + \sum_{g=1}^{G} \beta_g y_{g,it} + \sum_{\omega=1}^{\Omega} \beta_\omega \tilde{y}_{\omega,it} \\
&\quad + \frac{1}{2} \sum_{m=1}^{M} \sum_{m\prime=1}^{M} \beta_{mm\prime} x_{m,it} x_{m\prime,it} + \frac{1}{2} \sum_{n=1}^{N} \sum_{n\prime=1}^{N} \beta_{nn\prime} \tilde{x}_{n,it} \tilde{x}_{n\prime,it} \\
&\quad + \frac{1}{2} \sum_{g=1}^{G} \sum_{g\prime=1}^{G} \beta_{gg\prime} y_{g,it} y_{g\prime,it} + \frac{1}{2} \sum_{\omega=1}^{\Omega} \sum_{\omega\prime=1}^{\Omega} \beta_{\omega\omega\prime} \tilde{y}_{\omega,it} \tilde{y}_{\omega\prime,it} \\
&\quad + \sum_{m=1}^{M} \sum_{n=1}^{N} \beta_{mn} x_{m,it} \tilde{x}_{n,it} + \sum_{m=1}^{M} \sum_{g=1}^{G} \beta_{mg} x_{m,it} y_{g,it} + \sum_{m=1}^{M} \sum_{\omega=1}^{\Omega} \beta_{m\omega} x_{m,it} \tilde{y}_{\omega,it} \\
&\quad + \sum_{n=1}^{N} \sum_{g=1}^{G} \beta_{ng} \tilde{x}_{n,it} y_{g,it} + \sum_{n=1}^{N} \sum_{\omega=1}^{\Omega} \beta_{n\omega} \tilde{x}_{n,it} \tilde{y}_{\omega,it} + \sum_{g=1}^{G} \sum_{\omega=1}^{\Omega} \beta_{g\omega} y_{g,it} \tilde{y}_{\omega,it} + \epsilon_{it}, \qquad (2.1)
\end{aligned}$$

where

$$\epsilon_{it} = v_{it} - \mu_{it}, \qquad (2.2)$$

ϵ_{it} can be decomposed into a one-sided error, μ_{it}, and a standard noise component, v_{it}, with zero mean. Substituting equation (2.2) into equation (2.1), I obtain,

$$0 = \overrightarrow{D}_{\tau} + v_{it} - \mu_{it}. \qquad (2.3)$$

Next I subtract the plant-specific effect, $\gamma_p d_p$, from the one-sided error component to model the plant-specific effect explicitly in the directional distance function, and then set it equal to zero to represent frontier production. The directional distance function to be estimated can be re-written as

$$\begin{aligned}
0 &= \overrightarrow{D}_{\tau} + v_{it} - (\mu_{it} - \gamma_p d_p) - \gamma_p d_p \\
&= \overrightarrow{D}_{\tau} - \gamma_p d_p + v_{it} - \mu_{it}^{*}, \qquad (2.4)
\end{aligned}$$

where $\mu_{it}^{*} = \mu_{it} - \gamma_p d_p$.

The translation property for equation (2.1) can be written as

$$\overrightarrow{D}_{\tau}(\mathbf{x} - \alpha \mathbf{g}_x, \tilde{\mathbf{x}} - \alpha \mathbf{g}_{\tilde{x}}, \mathbf{y} + \alpha \mathbf{g}_y, \tilde{\mathbf{y}} - \alpha \mathbf{g}_{\tilde{y}}) = \overrightarrow{D}_{\tau}^{t}(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}) - \alpha \qquad (2.5)$$

Here, without loss of generality, I choose the direction vector as (-1, -1, 1, -1) and, to satisfy translation property, the following restrictions are applied:

$$\begin{aligned}
\sum_{g=1}^{G}\beta_g - \sum_{m=1}^{M}\beta_m - \sum_{n=1}^{N}\beta_n - \sum_{\omega=1}^{\Omega}\beta_\omega &= -1, \\
\sum_{g=1}^{G}\beta_{gg\prime} - \sum_{m=1}^{M}\beta_{mg\prime} - \sum_{n=1}^{N}\beta_{ng\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega g\prime} &= 0, \forall g\prime \\
\sum_{g=1}^{G}\beta_{g\omega\prime} - \sum_{m=1}^{M}\beta_{m\omega\prime} - \sum_{n=1}^{N}\beta_{n\omega\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega\omega\prime} &= 0, \forall \omega\prime \\
\sum_{g=1}^{G}\beta_{gm\prime} - \sum_{m=1}^{M}\beta_{mm\prime} - \sum_{n=1}^{N}\beta_{nm\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega m\prime} &= 0, \forall m\prime \\
\sum_{g=1}^{G}\beta_{gn\prime} - \sum_{m=1}^{M}\beta_{mn\prime} - \sum_{n=1}^{N}\beta_{nn\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega n\prime} &= 0, \forall n\prime. \qquad (2.6)
\end{aligned}$$

To examine the effect of industry restructuring on technological efficiency, I revise equation (2.1) by adding the time-varying restructuring dummy, $Restr$, and interacting it with input and output variables. Therefore, the equation can be written as

$$\begin{aligned}
0 &= \overrightarrow{D}^t_\tau(\mathbf{x}_{it}, \tilde{\mathbf{x}}_{it}, \mathbf{y}_{it}, \tilde{\mathbf{y}}_{it}; -g_x, -g_{\tilde{x}}, g_y, -g_{\tilde{y}}) + \epsilon_{it} \\
&= \alpha_0 + \gamma Restr + \sum_{m=1}^{M} x_{m,it}(\beta_m + \gamma_m Restr) + \sum_{n=1}^{N}\tilde{x}_{n,it}(\beta_n + \gamma_n Restr) \\
&\quad + \sum_{g=1}^{G} y_{g,it}(\beta_g + \gamma_g Restr) + \sum_{\omega=1}^{\Omega}\tilde{y}_{\omega,it}(\beta_\omega + \gamma_\omega Restr) \\
&\quad + \frac{1}{2}\sum_{m=1}^{M}\sum_{m\prime=1}^{M}\beta_{mm\prime}x_{m,it}x_{m\prime,it} + \frac{1}{2}\sum_{n=1}^{N}\sum_{n\prime=1}^{N}\beta_{nn\prime}\tilde{x}_{n,it}\tilde{x}_{n\prime,it} \\
&\quad + \frac{1}{2}\sum_{g=1}^{G}\sum_{g\prime=1}^{G}\beta_{gg\prime}y_{g,it}y_{g\prime,it} + \frac{1}{2}\sum_{\omega=1}^{\Omega}\sum_{\omega\prime=1}^{\Omega}\beta_{\omega\omega\prime}\tilde{y}_{\omega,it}\tilde{y}_{\omega\prime,it} \\
&\quad + \sum_{m=1}^{M}\sum_{n=1}^{N}\beta_{mn}x_{m,it}\tilde{x}_{n,it} + \sum_{m=1}^{M}\sum_{g=1}^{G}\beta_{mg}x_{m,it}y_{g,it} + \sum_{m=1}^{M}\sum_{\omega=1}^{\Omega}\beta_{m\omega}x_{m,it}\tilde{y}_{\omega,it} \\
&\quad + \sum_{n=1}^{N}\sum_{g=1}^{G}\beta_{ng}\tilde{x}_{n,it}y_{g,it} + \sum_{n=1}^{N}\sum_{\omega=1}^{\Omega}\beta_{n\omega}\tilde{x}_{n,it}\tilde{y}_{\omega,it} + \sum_{g=1}^{G}\sum_{\omega=1}^{\Omega}\beta_{g\omega}y_{g,it}\tilde{y}_{\omega,it} + \epsilon_{it}, \qquad (2.7)
\end{aligned}$$

To satisfy the translation property as in equation (2.5) and incorporating the restructuring effect, the restrictions are revised as follows:

$$\sum_{g=1}^{G}\beta_g - \sum_{m=1}^{M}\beta_m - \sum_{n=1}^{N}\beta_n - \sum_{\omega=1}^{\Omega}\beta_\omega = -1,$$

$$
\begin{aligned}
\sum_{g=1}^{G}\gamma_g - \sum_{m=1}^{M}\gamma_m - \sum_{n=1}^{N}\gamma_n - \sum_{\omega=1}^{\Omega}\gamma_\omega &= 0, \\
\sum_{g=1}^{G}\beta_{gg\prime} - \sum_{m=1}^{M}\beta_{mg\prime} - \sum_{n=1}^{N}\beta_{ng\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega g\prime} &= 0, \forall g\prime \\
\sum_{g=1}^{G}\beta_{g\omega\prime} - \sum_{m=1}^{M}\beta_{m\omega\prime} - \sum_{n=1}^{N}\beta_{n\omega\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega\omega\prime} &= 0, \forall \omega\prime \\
\sum_{g=1}^{G}\beta_{gm\prime} - \sum_{m=1}^{M}\beta_{mm\prime} - \sum_{n=1}^{N}\beta_{nm\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega m\prime} &= 0, \forall m\prime \\
\sum_{g=1}^{G}\beta_{gn\prime} - \sum_{m=1}^{M}\beta_{mn\prime} - \sum_{n=1}^{N}\beta_{nn\prime} - \sum_{\omega=1}^{\Omega}\beta_{\omega n\prime} &= 0, \forall n\prime.
\end{aligned} \tag{2.8}
$$

2.4.2 Partial Effects

To examine the partial effects along the frontier, of a change in one variable with respect to a change in another variable, I apply the implicit function theorem. For example, the impact of good output, y_g, upon good input, x_m, is

$$
\frac{d(y_g)}{d(x_m)} = -\frac{(\partial\overrightarrow{D}_0/\partial y_g)}{(\partial\overrightarrow{D}_0/\partial x_m)}, \forall g, m. \tag{2.9}
$$

Similarly, the partial effect between any pair of variables can be computed. As the partial derivatives can not be computed with respect to a dummy variable, to obtain the partial effects of restructuring on production, I compute the difference of fitted value of the directional distance with and without the restructuring dummy to approximate the partial derivatives of directional distance with respect to restructuring. I can obtain the partial effect of restructuring on good and bad inputs, good outputs, and emission levels, as follows:

$$
\begin{aligned}
\frac{d(x_m)}{d(Restr)} &= -\frac{(\overrightarrow{D}_0 - \overrightarrow{D}_0\prime)}{(\partial\overrightarrow{D}_0/\partial x_m)}, \forall m, \\
\frac{d(\tilde{x}_n)}{d(Restr)} &= -\frac{(\overrightarrow{D}_0 - \overrightarrow{D}_0\prime)}{(\partial\overrightarrow{D}_0/\partial \tilde{x}_n)}, \forall n, \\
\frac{d(y_g)}{d(Restr)} &= -\frac{(\overrightarrow{D}_0 - \overrightarrow{D}_0\prime)}{(\partial\overrightarrow{D}_0/\partial y_g)}, \forall g, \\
\frac{d(\tilde{y}_\omega)}{d(Restr)} &= -\frac{(\overrightarrow{D}_0 - \overrightarrow{D}_0\prime)}{(\partial\overrightarrow{D}_0/\partial \tilde{y}_\omega)}, \forall \omega,
\end{aligned} \tag{2.10}
$$

where $\overrightarrow{D}_{0'}$ denotes the fitted value of directional distance function without the restructuring effect.

2.4.3 Technical Efficiency and Productivity Change

Estimation of plant-specific PC, TC, and EC proceeds as follows. First, I estimate the directional distance function with a set of plant-specific dummies. The estimated equation from (2.4) is as follows:

$$0 = \hat{\overrightarrow{D}}_{\tau} - \hat{\gamma}_p d_p + \hat{v}_{pt} - \hat{\mu}^*_{pt}, \tag{2.11}$$

where $\hat{v}_{pt} - \hat{\mu}^*_{pt}$ is the residual and $\mu^*_{pt} = \mu_{pt} - \hat{\gamma}_p d_p$. Thus, $\hat{\mu}^*_{pt} - \hat{v}_{pt} = \hat{\overrightarrow{D}}_{\tau}$.

Following Cornwell, Schmidt, and Sickles (1990), to strip away the noise term, $\hat{v}_{it}$, I regress $\hat{\mu}_{it} - \hat{v}_{it}$ on a set of plant dummies and the interaction of plant dummy with time,

$$\hat{\epsilon}_{pt} = \alpha_0 + \sum_p \alpha_p d_p + \sum_p \theta_p d_p t + \phi_{pt}, \tag{2.12}$$

where ϕ_{pt} is a random error term assumed to be uncorrelated with the regressors. The fitted values of this regression are unbiased and consistent estimators (as T $\rightarrow \infty$) of μ_{pt}.

To obtain non-negative directional distances to measure inefficiency and define the frontier plant with a zero distance, I normalize $\hat{\mu}_{pt}$ by computing $\hat{\mu_{pt}}^s = \hat{\mu}_{pt} - \hat{\mu}_t$, where $\hat{\mu}_t = min_p\{\mu_{pt}\}\forall t$. From equation (2.1), for a given input or output ω, and its direction factor g_ω, $\hat{\mu_{pt}}^s g_\omega$ represents the shortfall in ω from the maximum (for good output) or the minimum (for the inputs or bad outputs) for plant p at time t, relative to the frontier. That is, $\hat{\mu_{pt}}^s$ is the non-random part of $\hat{\overrightarrow{D}}_{\tau}$. Next, I translate the estimated shortfall, $\hat{\mu_{pt}}^s g_\omega$, from a standardized unit back to its original unit as in ω, as follows:

$$\hat{\delta}_{\omega,pt} = |\hat{\mu}^s_{pt} g_\omega \hat{\sigma}_\omega| + \bar{\omega}, \tag{2.13}$$

where $\hat{\sigma}_\omega$ and $\bar{\omega}$ are respectively, the sample standard deviation and mean of ω. I take the absolute value of the first term, as the direction factor g_ω is positive for good output and negative for inputs and bad outputs. Therefore, the data transformation from equation (2.13) is at its lowest value for the frontier plant and the amount that is greater than the minimum value measures the amount of shortfalls. I then normalize these values again by computing $\hat{\delta}^{*}_{\omega,pt} = \hat{\delta}_{\omega,pt} - \hat{\delta}_{\omega,t}$, where $\hat{\delta}_{\omega,t} = min_{p}\{\hat{\delta}_{\omega,pt}\}\forall t$. That is, I subtract the smallest distance in each time period t such that the frontier plant has $\hat{\delta}^{*}_{\omega,\tau t} = 0$ and all other plants have $\hat{\delta}^{*}_{\omega,pt} > 0, p \neq \tau$.

To compute TE one needs to transform the values such that $0 < TE_{pt} \leq 1$, where the frontier plant has $TE_{\tau t} = 1$. One such transformation is described in the first chapter, and is given by equation (1.23), $exp(-\hat{\delta}^{*}_{\omega,pt})$. Following Agee, Atkinson, and Crocker (2012), I use a linear transformation to compute TE as

$$TE_{\omega,pt} = 1 - \hat{\delta}^{*}_{\omega,pt}/\omega_{\tau t}, \tag{2.14}$$

where $\omega_{\tau t}$ is the value of ω in its original unit for the frontier plant, which can also be estimated by $\omega_{pt} + \hat{\delta}^{*}_{\omega,pt}$. For example, to compute TE with respect to the good output, $\omega_{\tau t}$ denotes the frontier plant's total net electricity generations, which can be obtained by the sum of another plant's output level and the amount of its shortfall from the frontier. Therefore, equation (2.14) can be re-written as $TE_{\omega,pt} = \hat{\delta}^{*}_{\omega,pt}/(\omega_{pt} + \hat{\delta}^{*}_{\omega,pt})$. Thus, this linear transformation guarantees that the frontier plant has $TE_{\omega,\tau t} = 1$, and other plants have $TE_{\omega,pt}$ between 0 and 1.

I then compute the Luenberger productivity index, as described in equations (1.13) and (1.14), to measure Luenberger efficiency change and technical change, LEC and LTC. As discussed in Agee, Atkinson, and Crocker (2012), I modified these two equations by using the midpoint of the two directional distances to eliminate scaling issues of the direction vectors. Therefore, modified LEC and LTC are computed as follows:

$$LEC^{m} = \frac{\overrightarrow{D}_{o}^{t}(\mathbf{x}^{t}, \tilde{\mathbf{x}}^{t}, \mathbf{y}^{t}, \tilde{\mathbf{y}}^{t}) - \overrightarrow{D}_{o}^{t+1}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1})}{1/2[\overrightarrow{D}_{o}^{t}(\mathbf{x}^{t}, \tilde{\mathbf{x}}^{t}, \mathbf{y}^{t}, \tilde{\mathbf{y}}^{t}) + \overrightarrow{D}_{o}^{t+1}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1})]}, \tag{2.15}$$

and

$$LTC^{m} = \frac{1}{2}\{\frac{\overrightarrow{D}_{o}^{t+1}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1}) - \overrightarrow{D}_{o}^{t}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1})}{1/2[\overrightarrow{D}_{o}^{t+1}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1}) + \overrightarrow{D}_{o}^{t}(\mathbf{x}^{t+1}, \tilde{\mathbf{x}}^{t+1}, \mathbf{y}^{t+1}, \tilde{\mathbf{y}}^{t+1})]}$$

$$+\frac{\overrightarrow{D}_o^{t+1}(\mathbf{x}^t,\tilde{\mathbf{x}}^t,\mathbf{y}^t,\tilde{\mathbf{y}}^t)-\overrightarrow{D}_o^{t}(\mathbf{x}^t,\tilde{\mathbf{x}}^t,\mathbf{y}^t,\tilde{\mathbf{y}}^t)}{1/2[\overrightarrow{D}_o^{t+1}(\mathbf{x}^t,\tilde{\mathbf{x}}^t,\mathbf{y}^t,\tilde{\mathbf{y}}^t)+\overrightarrow{D}_o^{t}(\mathbf{x}^t,\tilde{\mathbf{x}}^t,\mathbf{y}^t,\tilde{\mathbf{y}}^t)]}\}. \tag{2.16}$$

Last, the percentage change Luenberger productivity change, LPC^m, is defined as

$$LPC^m = LTC^m + LEC^m. \tag{2.17}$$

2.5 Empirical Findings

Following equation (2.1) to (2.6), I first estimate the directional distance function with good inputs of labor, total fuel consumption, and capital expenditure, bad input of the sulfur content from coal and petroleum, good output of total net generation of electricity, and bad outputs of CO_2, SO_2, and NO_X emissions. That is, m=3, n=1, g=1, and $\omega = 3$. Next, I re-estimate the model by adding a time-varying restructuring dummy and interact it with the inputs and outputs variables, as specified in equations (2.7) and (2.8). Last, I estimate the model replacing total fuel consumption by the consumption of three types of fuel, coal, petroleum, and gas, to capture the effect of different fuel types or fuel switching on technical efficiency. Therefore, in the third model specification, m=5, n=1, g=1, and $\omega = 3$, I allow the restructuring dummy to interact with all input and output variables.

Table (2.10) reports the estimation results from the three model specifications. The second column, regression (1), shows the estimation results from the first model specification. All four inputs, capital, fuel, labor, and sulfur content, have positive coefficients and are statistically significant. That is, increasing the inputs will increase the distance from the frontier, controlling for all other factors. Furthermore, fuel input has the greatest impact on the change of directional distances compared to other inputs, with sulfur content from the fuel being the second-largest factor. This is consistent with the model specification, since three types of emissions are included in the directional distance equation as negative factors on the distances. The second-order terms of the inputs, capital, labor, and sulfur, are negative and statistically significant, indicating their effects on efficiency are positive but decreasing. The coefficient on electricity generation output is -0.349; that is, the more output a plant can generate, given the level of inputs, the more efficient it is. Among the emissions, CO_2 has the largest effect. The coefficient on SO_2 emissions, although negative and statistically significant, is very small in magnitude. The effect of NO_X emission is not significant at the 5% level.

The third column in Table (2.10) shows the estimation results from the second model specification where a time-varying dummy indicates the restructuring status. The estimated coefficients are very similar to the first model for a majority of the variables. The coefficient on the restructuring dummy indicates a small positive effect on the directional distance, and is statistically significant at the 10% level. It implies that plants located in the areas subject to industry deregulation and restructuring are generally slightly less efficient. This result is consistent with some previous studies, such as Goto et al. (2008). The coefficients on the interactions of restructuring with all inputs, output, and emissions are generally insignificant, except for the coefficient on the interaction of restructuring with labor, which is negative but has very small magnitude.

Regression (3) in the last column reports the estimation results when total fuel consumption is further broken down into the three fuel types. All three coefficients on the fuel inputs are positive and statistically significant, with coal having the largest coefficient. All other inputs, including capital, labor, and sulfur content, also have positive signs and are significant at the 5% level, consistent with the previous two regressions. The coefficient on electricity output is -0.235 and statistically significant, consistent with business intuition and with the previous two models. The estimated effects of emissions are not precisely estimated. The restructuring effect and its interaction with the inputs and output variables are insignificant. The relative magnitude of all of the precisely estimated coefficients suggests that, given the equal weight of the directional vector, (-1, -1, 1, -1), coal consumption has the largest impact on the directional distance and on efficiency. Therefore, for those plants whose primary fuel type is coal, the quality of coal in terms of heat content and sulfur content would largely determine their efficiency level.

Table 2.10: Directional Distance Function Estimation Results

	Coefficients (t-value)		
Variable	Reg (1)	Reg (2)	Reg (3)
Intercept	0.224	0.222	0.184
	(9.917)**	(9.744)**	(14.692)**
Restructure		0.007	0.002
		(1.816)	(1.032)
Input:			
Fuel	0.280	0.278	
	(20.002)**	(19.212)**	
Fuel*Fuel	-0.029	-0.019	
	(-0.836)	(-0.561)	
Fuel*Restructure		0.026	
		(1.000)	
Coal			0.391
			(35.845)**
Coal*Coal			0.037
			(1.758)
Coal*Restructure			0.032
			(1.571)
Coal*Gas			0.114
			(14.674)**
Coal*Petroleum			0.072
			(6.456)**
Gas			0.145
			(26.366)**
Gas*Gas			-0.001
			(-0.385)
Gas*Restructure			0.000
			(0.099)
Gas*Petroleum			0.012
			(1.053)
Petroleum			0.148
			(24.339)**
Petroleum*Petroleum			-0.010
			(-5.608)**

	Coefficients (t-value)		
Variable	Reg (1)	Reg (2)	Reg (3)
Petroleum*Restructure			0.008
			(2.055)**
Capital	0.066	0.068	0.028
	(10.665)**	(10.561)**	(8.098)**
Capital*Fuel	0.045	0.044	
	(4.029)**	(3.914)**	
Capital*Coal			0.003
			(0.437)
Capital*Gas			-0.004
			(-1.396)
Capital*Petroleum			0.002
			(0.553)
Capital*Capital	-0.009	-0.010	-0.002
	(-4.036)**	(-4.039)**	(-1.774)
Capital*Labor	0.041	0.041	0.001
	(11.964)**	(11.591)**	(0.339)
Capital*Restructure		0.010	-0.002
		(1.579)	(-0.512)
Labor	0.052	0.055	0.017
	(9.863)**	(10.318)**	(6.034)**
Labor*Fuel	-0.084	-0.086	
	(-8.891)**	(-8.696)**	
Labor*Coal			-0.020
			(-3.900)**
Labor*Gas			-0.004
			(-1.808)
Labor*Petroleum			-0.001
			(-0.460)
Labor*Labor	-0.009	-0.009	-0.003
	(-7.299)**	(-7.295)**	(-4.751)**
Labor*Restructure		-0.009	-0.001
		(-3.329)**	(-0.776)
Sulfur	0.106	0.107	0.052
	(8.810)**	(8.627)**	(5.750)**
Sulfur*Restructure		-0.010	-0.005

Variable	Coefficients (t-value) Reg (1)	Reg (2)	Reg (3)
		(-1.857)	(-1.611)
Sulfur*Sulfur	-0.026	-0.024	-0.002
	(-4.822)**	(-4.460)**	(-0.714)
Output:			
Electricity	-0.349	-0.345	-0.235
	(-61.549)**	(-60.179)**	(-54.389)**
Electricity*Electricity	0.003	0.002	0.067
	(1.330)	(0.881)	(19.770)**
Electricity*Restructure		-0.006	0.003
		(-1.883)	(1.090)
Fuel*Electricity	0.012	0.012	
	(1.720)	(1.693)	
Coal*Electricity			0.016
			(2.666)**
Gas*Electricity			-0.015
			(-2.435)**
Petroleum*Electricity			0.063
			(20.291)**
Capital*Electricity	0.007	0.006	-0.007
	(3.277)**	(2.658)**	(-3.073)**
Labor*Electricity	0.014	0.014	-0.006
	(6.839)**	(6.501)**	(-2.450)**
Sulfur*Electricity	-0.001	-0.001	0.032
	(-0.244)	(-0.162)	(3.791)**
Emissions:			
CO_2	0.171	0.174	0.010
	(10.389)**	(10.445)**	(1.010)
CO_2*CO_2	-0.038	-0.039	0.099
	(-1.077)	(-1.080)	(5.159)**
CO_2*Restructure		-0.021	-0.037
		(-0.732)	(-1.629)
CO_2*NO_X	-0.029	-0.029	-0.011
	(-2.319)**	(-2.254)**	(-1.616)
Fuel*CO_2	0.040	0.037	
	(1.318)	(1.199)	

	Coefficients (t-value)		
Variable	Reg (1)	Reg (2)	Reg (3)
Coal*CO_2			-0.140
			(-8.477)**
Petroleum*CO_2			-0.053
			(-6.370)**
Gas*CO_2			0.023
			(2.545)**
Capital*CO_2	-0.030	-0.031	0.001
	(-2.919)**	(-2.947)**	(0.268)
Labor*CO_2	0.013	0.016	0.029
	(1.174)	(1.385)	(4.383)**
Sulfur*CO_2	-0.005	-0.006	0.036
	(-0.332)	(-0.347)	(4.090)**
Fuel*NO_X	0.017	0.016	
	(1.485)	(1.347)	
Coal*NO_X			0.008
			(1.301)
Gas*NO_X			-0.007
			(-1.451)
Petroleum*NO_X			0.026
			(4.013)**
Fuel*Sulfur	0.023	0.025	
	(1.292)	(1.400)	
Coal*Sulfur			-0.068
			(-5.731)**
Petroleum*Sulfur			0.075
			(4.526)**
Fuel*SO_2	0.001	-0.004	
	(0.063)	(-0.308)	
Coal*SO_2			0.010
			(1.311)
Petroleum*SO_2			-0.059
			(-7.667)**
Capital*NO_X	-0.002	0.001	0.000
	(-0.710)	(0.210)	(-0.135)
Capital*Sulfur	-0.024	-0.026	-0.005

Variable	Coefficients (t-value) Reg (1)	Reg (2)	Reg (3)
	(-5.263)**	(-5.317)**	(-1.803)**
Capital*SO_2	-0.012	-0.013	-0.002
	(-4.585)**	(-4.394)**	(-1.379)
Labor*NO_X	0.029	0.027	-0.001
	(9.477)**	(8.599)**	(-0.346)
Labor*Sulfur	0.024	0.025	-0.007
	(3.942)**	(3.993)**	(-1.973)**
Labor*SO_2	0.001	0.001	0.001
	(0.291)	(0.288)	(1.196)
NO_X	-0.004	-0.005	0.005
	(-0.767)	(-0.920)	(1.487)
NO_X*Restructure		-0.008	0.005
		(-0.668)	(0.771)
NO_X*NO_X	0.001	0.002	-0.003
	(0.287)	(0.330)	(-1.126)
Electricity*CO_2	-0.043	-0.042	0.003
	(-5.995)**	(-5.746)**	(0.510)
Electricity*NO_X	0.012	0.012	0.008
	(7.231)**	(7.062)**	(2.588)**
Electricity*SO_2	0.001	0.001	-0.028
	(0.667)	(0.372)	(-6.914)**
Sulfur*NO_X	-0.005	-0.006	-0.003
	(-2.342)**	(-2.660)**	(-2.538)**
Sulfur*SO_2	0.012	0.011	0.004
	(2.651)**	(2.467)**	(1.723)
SO_2	-0.019	-0.021	-0.031
	(-2.468)**	(-2.727)**	(-6.357)**
SO_2*CO_2	0.006	0.008	0.019
	(0.539)	(0.690)	(2.796)**
SO_2*Restructure		0.007	0.004
		(1.817)	(1.654)
SO_2*NO_X	0.000	0.002	-0.002
	(0.024)	(0.754)	(-1.381)
SO_2*SO_2	-0.006	-0.005	0.001
	(-1.327)	(-1.045)	(0.325)

Note: Double asterisk indicates significance at the .05 level

To examine further the partial relationships among variables along the frontier, I compute the partial effect as described in equations (2.9) and (2.10) and summarize the average effect in table (2.11). The estimated average partial effects from the first two regression models are very similar, as the only difference in their functional forms are the inclusion of the restructuring dummy and its interaction with inputs and outputs. For example, EXPK_QE denotes the partial effect of electricity generation output(QE) with respect to capital expenditure (EXPK). The average partial effects computed from the first two models are about 0.2, suggesting that to increase electricity output the plants need to increase their capital expenditure. Similar results hold true for the partial effect on electricity generation with respect to changes in the labor input, the fuel input, and the sulfur content in fuel consumption. The magnitude of the partial effect on electricity output with respect to the fuel input is around 0.8, much larger than the other three, and indicates that, for power plants to increase their electricity output, they must increase their fuel input more than the other inputs. This is consistent with the production characteristics that once the generation capacity is built, power plants rely more on adjusting fuel consumption levels and the utilization of existing capacity to change their output level. The partial effect computed from the third model suggests that coal is the major factor contributing to changes in output level.

Table 2.11: Average Partial Effects

	Reg (1)	Reg (2)	Reg (3)
EXPK_QE	0.20 (0.183)	0.21 (0.184)	0.08 (0.990)
QL_QE	0.15 (0.126)	0.15 (0.125)	0.09 (2.982)
QF_QE	0.79 (0.328)	0.81 (0.332)	
QCOAL_QE			1.36 (18.997)
QGAS_QE			-1.13 (66.658)
QPETRO_QE			-2.62 (123.725)
QS_QE	0.31 (0.134)	0.31 (0.133)	-0.10 (8.354)
EXPK_QSO2	2.01 (64.218)	5.79 (92.705)	1.81 (4.658)
QL_QSO2	3.06 (49.178)	2.58 (22.518)	1.26 (9.250)

	Reg (1)	Reg (2)	Reg (3)
QF_QSO2	8.52 (287.136)	23.76 (464.568)	
QCOAL_QSO2			21.89 (35.025)
QPETRO_QSO2			10.73 (135.063)
QS_QSO2	3.20 (118.179)	8.91 (147.863)	2.01 (10.566)
EXPK_QNOX	104.90 (4711.377)	0.48 (70.468)	-6.23 (198.282)
QL_QNOX	53.01 (2291.138)	1.15 (70.328)	-2.77 (134.574)
QF_QNOX	368.93 (16315.148)	6.16 (289.861)	
QCOAL_QNOX			-68.41 (2194.904)
QGAS_QNOX			-11.99 (827.699)
QPETRO_QNOX			-10.44 (885.594)
QSO2_QE	-0.06 (0.035)	-0.06 (0.034)	0.10 (6.002)
QCO2_QE	0.50 (0.263)	0.50 (0.269)	-0.34 (16.905)
QNOX_QE	-0.01 (0.115)	-0.01 (0.108)	-0.03 (2.431)
EXPK_RESTR		-8.23 (53.795)	-33.01 (532.144)
QL_RESTR		-2.93 (7.577)	-20.69 (304.650)
QF_RESTR		-23.57 (69.780)	
QCOAL_RESTR			-606.41 (10544.567)
QGAS_RESTR			-137.29 (1550.658)
QPETRO_RESTR			-142.45 (1697.113)
QS_RESTR		-10.36 (52.408)	-41.60 (742.374)
QE_RESTR		32.07 (122.542)	336.66 (5607.400)
QSO2_RESTR		1.46 (5.046)	22.22 (332.916)
QCO2_RESTR		-18.31 (83.868)	24.63 (186.666)
QNOX_RESTR		0.56 (12.974)	-3.86 (39.551)

Note: Standard Deviation in parentheses.

In the first two models, the partial effects on emissions levels of changes in the input or output variables are not precisely estimated, as the estimated average effects have very large standard errors. The average partial effects on electricity generation with respect to the three type of emissions, SO_2, CO_2, and NO_X, are -0.06, 0.50, and -0.02, respectively. The partial effects on SO_2 and NO_X are negative and very small in magnitude, which suggest that increasing electricity generation does not necessarily increase SO_2 and NO_X emission levels. In other words, with recent stringent environmental regulatory policies and improved emission control technologies, plants managed to generate more electricity with slightly fewer emissions of these two pollutants. However, as CO_2 or greenhouse gas has not yet been regulated in the power generating industry, shows that the increased level of electricity output is accompanied by an increased level of CO_2 emissions. Some of these partial effects estimated from the third model have a sign opposite from the first two models; however, they also have larger standard errors.

In this table I also report the average partial effects of restructuring with respect to production inputs, outputs, and emissions. The results from regression (2) and (3) are mostly consistent. The average partial effects of restructuring with respect to the input variables are negative, which indicates that the states that passed deregulation legislation and implemented restructuring are more likely to decrease their inputs. This is consistent with the story described in the background section that many firms and plants are forced to divest their generation capacities during deregulation and restructuring. Meanwhile, the partial effect of restructuring with respect to electricity output is positive but with a large standard deviation. As for the impact on emission levels, plants in restructuring states may have slightly higher levels of SO_2 and NO_X emissions. This finding is consistent with some previous studies that plants in those deregulation-active states are less likely to invest in R&D and innovations, including investing in pollution control research, than those in the states that are subject to rate-of-return regulations. Therefore, competitive deregulations and restructuring have negative impact on emission reduction.

Table (2.12) shows the list of frontier plants for each year,as estimated by the first two regression models. With or without controlling for the restructuring effect, the two models yield the same list of frontier plants. Between 1998 to 2001, Turkey Point Plant in the Florida Power and Light Company is the frontier plant. In the following year, H B Robinson of Carolina Power & Light Co and Fort St. Vrain of the Public Service Co. of Colorado became the frontier plants. The table also shows the plant capacity and total net generation.

Table 2.12: Frontier Plants: Regression (1) and (2)

Year	Plant Code	Utility Name	Plant Name	Capacity	Net Generation
1998	621	Florida Power & Light Co	Turkey Pt	2324	15,123,867
1999	621	Florida Power & Light Co	Turkey Pt	2324	15,289,253
2000	621	Florida Power & Light Co	Turkey Pt	2324	14,616,888
2001	621	Florida Power & Light Co	Turkey Pt	804	3,195,454
2002	3251	Carolina Power & Light Co	H B Robinson	207	1,021,063
2003	6112	Public Service Co of Colorado	Fort St Vrain	343	3,917,348
2004	6112	Public Service Co of Colorado	Fort St Vrain	343	1,387,252
2005	6112	Public Service Co of Colorado	Fort St Vrain	343	1,614,210

Table (2.13) lists the frontier plants estimated from regression (3). It is slightly different from table (2.12) in the earlier years, but overall two common power plants show up as frontier plants.

Table 2.13: Frontier Plants: Regression (3)

Year	Plant Code	Utility Name	Plant Name	Capacity	Net Generation
1998	3251	Carolina Power & Light Co	H B Robinson	976	6,418,814
1999	3251	Carolina Power & Light Co	H B Robinson	976	6,654,642
2000	3251	Carolina Power & Light Co	H B Robinson	976	7,256,218
2001	3251	Carolina Power & Light Co	H B Robinson	207	916,656
2002	6112	Public Service Co of Colorado	Fort St Vrain	336	4,664
2003	6112	Public Service Co of Colorado	Fort St Vrain	343	3,917,348
2004	6112	Public Service Co of Colorado	Fort St Vrain	343	1,387,252
2005	6112	Public Service Co of Colorado	Fort St Vrain	343	1,614,210

To further understand the frontier plants, I show their fuel consumption in table (2.14). According to the directional distance functions, increased sulfur content or emissions contribute to a larger distance from the frontier. Since coal and petroleum contain sulfur, and gas contains no sulfur, the power plants that rely more heavily on coal and petroleum have higher levels of SO_2 emissions and get punished more heavily by the directional distance functions. The frontier plants, except for H B Robinson, did not consume coal. Fort St. Vrain only consumed gas for its power generation.

Table 2.14: Fuel Consumption by Frontier Plants

	Plant				Coal Quality		Gas Quality	Petroleum Quality	
Year	Code	Coal	Gas	Petroleum	Heat	Sulfur	Heat	Heat	Sulfur
1998	621	0	13,504	3,287			1,000	150,835	1.29%
1998	3251	364	0	5	12,104	1.36%		139,583	0.21%
1999	621	0	13,621	3,178			1,000	151,109	1.00%
1999	3251	371	0	3	12,851	1.41%		139,478	0.03%
2000	621	0	12,912	3,126			1,000	152,102	0.99%
2000	3251	395	0	5	12,754	1.05%		138,923	0.04%
2001	621	0	12,837	2,945			1,000	151,864	0.99%
2001	3251	361	0	2	12,610	1.23%		139,796	0.05%
2002	3251	403	0	3	12,588	1.07%		140,564	0.04%
2002	6112	0	2,013	0	0	0	999		
2003	6112	0	1,594	0	0	0	993		
2004	6112	0	908	0	0	0	990		
2005	6112	0	1,400	0	0	0	1,000		

The results from the three regressions show that with the equal-weight direction vector (1, 1, -1, 1), the model punishes the plants that have a large portion of coal input and favors those plants with smaller capacity that rely more on natural gas generation. These rankings in terms of estimated directional distances can be arbitrary depending on the choice of the weights in the direction vectors. Especially the third regression yields coefficient estimates that are either in sign inconsistent with business intuition or are insignificant. Therefore, it is more meaningful to examine the efficiency change at an aggregate level.

Table (2.15) reports average Luenberger EC, TC, and PC weighted by plants' total electricity generation for all the plants over the sample period. To focus on the restructuring effect on EC, TC, and PC, table (2.15) compares the results from regressions (1) and (2) where the production function is the same, except that regression (2) differs from (1) by adding the restructuring dummy and its interactions. The year of EC, TC, and PC denotes the starting year for the one-year growth calculations. Both models show a similar decreasing trend, with positive values in the first couple of years, then a decrease to marginally negative changes in the later years, as the total number of plants falls rapidly at the same time. The second model, which controls for the restructuring effect, yields slightly higher EC, TC, and PC.

Table 2.15: Average EC, TC, and PC by Year

	Num of	Reg (1): Base Model			Reg (2): Base + Restructure		
Year	Plants	EC	TC	PC	EC	TC	PC
1998	352	0.0285	0.0202	0.0487	0.0298	0.0206	0.0504
1999	326	0.0259	-0.0203	0.0057	0.0254	-0.0197	0.0058
2000	284	-0.0317	0.0223	-0.0094	-0.0292	0.0144	-0.0148
2001	276	-0.0036	-0.0081	-0.0117	-0.0016	-0.0071	-0.0087
2002	265	-0.0014	0.0001	-0.0013	-0.0003	-0.0006	-0.0009
2003	258	-0.0028	-0.0064	-0.0092	-0.0011	-0.0067	-0.0078
2004	255	-0.0111	-0.0199	-0.0311	-0.0098	-0.0178	-0.0276

Table (2.16) summarizes the weighted average EC, TC, and PC by state-level deregulation status to which the plants are subject. The number of plants in non-deregulation states decreased from over 300 in 1998 to below 200 in 2004. Meanwhile, only a limited number of plants were subjected to deregulation legislation in the earlier years and then the number increases substantially since 2001. In 2000 only 14 plants are subject to deregulation. A drop in the number of plants subject to deregulation in 2000 is due to certain states, such as California, suspending their deregulation process after the blackout incidents and failing to lower retail prices. From 1998 to 1999 the results from both models suggest productivity improvements with efficiency changes, or the catching-up effect, as the main driver of the growth. EC, TC, and PC are higher in the deregulation-active states as compared to the non-deregulation states. Between 2001 and 2004, the number of plants that are in deregulation-active states is relatively stable at over 70. A similar declining trend in EC, TC, and PC for both groups of plants is observed. The results from the first model show that TC is about the same for the two groups, EC is lower in deregulation-active states in 2001 and 2002 and then became higher since 2003. The second model shows a bigger difference between the two groups; between 2002 and 2004, both EC and TC in the deregulation-active states are higher than the non-deregulation group, and therefore higher PC is observed in the deregulation-active states as well. One can further break down the results by regions or states to examine the productivity and efficiency changes from different geographical and legislative aspects.

Table 2.16: Average EC, TC, and PC by Year and Restructuring Status

	Num of	Reg (1): Base Model			Reg (2): Base + Restructure		
Year	Plants	EC	TC	PC	EC	TC	PC
Non-Deregulation							
1998	324	0.0289	0.0203	0.0492	0.0298	0.0209	0.0507
1999	276	0.0268	-0.0203	0.0065	0.0261	-0.0196	0.0065
2000	270	-0.0324	0.0224	-0.0100	-0.0298	0.0144	-0.0154
2001	203	0.0031	-0.0081	-0.0050	0.0032	-0.0053	-0.0021
2002	189	-0.0013	0.0001	-0.0012	-0.0007	-0.0011	-0.0018
2003	188	-0.0078	-0.0064	-0.0142	-0.0079	-0.0056	-0.0135
2004	180	-0.0158	-0.0199	-0.0357	-0.0158	-0.0181	-0.0339
Deregulation Active							
1998	28	0.0173	0.0187	0.0360	0.0315	0.0132	0.0446
1999	50	-0.0330	-0.0177	-0.0507	-0.0216	-0.0247	-0.0464
2000	14	0.0393	0.0197	0.0590	0.0388	0.0120	0.0508
2001	73	-0.0277	-0.0081	-0.0358	-0.0188	-0.0132	-0.0319
2002	76	-0.0016	0.0001	-0.0015	0.0010	0.0007	0.0017
2003	70	0.0126	-0.0065	0.0061	0.0197	-0.0101	0.0096
2004	75	0.0017	-0.0199	-0.0181	0.0068	-0.0170	-0.0102

2.6 Conclusions

This chapter estimates directional distance functions of multiple-input, multiple-output production in the fossil-fuel electricity power plants. Based on the 78 electric utility sample data studied in the first chapter, I constructed a dataset of 377 plants containing additional production information aggregated from boiler and generator level. The sample covers 1998 to 2005, during which a wave of restructuring activities took place as a response to deregulation policies. Along the frontier I compute the partial effect of restructuring and find that plants that are subject to deregulation tend to decrease their inputs, including capital expenditure, labor and fuel. However, these reductions do not necessarily lower their emissions. This finding is consistent with some previous literature that deregulation increases emissions. In addition, I apply the Luenberger index approach to compute plants' technical efficiency change and productivity change and show that, overall, there is a declining trend in productivity and efficiency changes within my sample period. However, the plants in deregulation-active states have slightly higher PC and EC compared to those in the non-deregulation states.

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Appendix A

Data source and computation methodology

A.1 Environmental performance measures

In this paper, the environmental performance of the electric utility firms is measured by the actual emission levels of CO_2, SO_2, and NO_X (in tons), then adjusted for firm size, which is measured by the total amount of electricity generated (in kWh). The air pollution data for the years 1988–1997 are directly obtained from the EIA. The annual data of the subsequent years in the sample are calculated following the methodology described in *EIA Electric Power Annual*, since the EIA discontinued releasing the emissions data to the public. The Environmental Protection Agency (EPA) reports emission levels of CO_2, SO_2 and NO_X every 5 years. The emission data calculated in this study are consistent with the EPA data.

A. Estimate CO_2 emissions:

Based on the methodology in *EIA Electric Power Annual*, CO_2 emissions are estimated as:

$$\begin{aligned} CO_2 emissions(tons) &= fuel\ consumption(MMBtu) \times emission\ factor(pounds/MMBtu) \\ &\quad \times incomplete\ combustion\ factor \times \frac{tons}{pounds}. \end{aligned} \tag{A.1}$$

- Fuel consumption

  Fuel consumption measured in physical units can be converted into millions of Btu (MMBtu) based on the heat content of the type and quality of the fuels. The plant-level data on heat content of fuel consumption are available in EIA-920/906, column "year-to-date electric fuel consumption MMBtus" since 2001. However, prior to 2001, fuel consumption is only reported in physical units in EIA-920. I convert these data to heat content in MMBtu based on the methodology described in "Carbon Dioxide Emissions from the Generation of Electric Power in the United States, EIA 1999, Appendix B":

  – Step one: Sum of monthly consumption (FERC-423) times monthly average Btu content (FERC-423) divided by total annual consumption (FERC-423)= Weighted Annual BTU Content Factor.
  – Step two: Annual Consumption (EIA-920) times Weighted Annual BTU Content Factor (from step 1) = Annual BTU Consumption. For those firms that report fuel consumption in EIA-920 but not heat content information in FERC-423, I replace the missing values with the state weighted-average of BTU content factor based on the geographic locations of the plants; if the state average is not available, the national weighted-average of BTU content factor is applied instead.

- Fuel-specific emission factor

  The fuel-specific emission factor is reported in "Table A1 Sulfur Dioxide, Nitrogen Oxide, and Carbon Dioxide Emissions Factors," and "Table A2 Carbon Dioxide Emission Factors for Coal by Rank and State of Origin," *Electric Power Annual* (2003) for the years prior to 2001. These emission factors are revised in 2001 as shown in "Table A3" in *Electric Power Annual* (2006). I obtain the emission factor by matching the fuel type and state of origin with those in EIA-920/906. As the emission factor is measured in pounds per MMBtu, I divide the emission level by 2000 to convert pounds to short tons.

- Incomplete combustion factor

  According to *Electric Power Annual*, the incomplete combustion factor is 0.995 for natural gas and 0.99 for all other types of fuels.

B. Estimate SO_2 emissions:

Following *EIA Electric Power Annual* (2003, 2006), Appendix A, I calculate SO_2 emissions as

$$\begin{aligned} SO_2\ emissions(tons) &= fuel\ consumption\ (tons\ for\ solids, barrels\ for\ liquids, \\ &\quad thousand\ cubic\ feet\ for\ gases) \\ &\quad \times emission\ factor(pounds\ per\ ton, barrel, or\ Mcf) \\ &\quad \times sulfur\ content \times (1 - FGD\ efficiency\ percentage) \\ &\quad \times \frac{tons}{pounds}. \end{aligned} \tag{A.2}$$

- Fuel consumption

  Fuel consumption is taken from Form EIA-920/906, column of "year-to-date electric fuel consumption quantity," reported in short tons for solids, thousands of cubic feet for gases, and barrels for liquids.

- Combustion system type

  Information on combustion system type is collected by EIA-767, in F767_Bdesign file (prior to 2001) and F767_boiler file (from 2001), where every facility reports the fuel type, the combustion system type in each of its boilers. Up to three fuel types and three combustion system types (also known as "firing type") are reported according to the predominance in its production. When a boiler reports multiple firing type, I only use the first primary firing type in my computation because there is not enough information on how much fuel is consumed by each firing type.

- Emission factor

  The emission factor for SO_2 emissions depends upon fuel type and combustion system type. It is available in Table A1, *Electric Power Annual* (2003) for data prior to 2001 and revised in 2001, reported in *Electric Power Annual* (2006). The emission factors are measured in pounds per ton, pounds per MMCF, or pounds per MG, depending on the fuel type and firing type. Proper unit conversion is done so as to be consistent with fuel consumption in EIA-920. The steam electric plants that did not report in Form EIA-767 are assumed to have a dry-bottom, non-cyclone boiler using a firing method that falls into the "All Other" category shown on Table A1.

- Sulfur content

  Table A1 in *Electric Power Annual* also indicates the fuel types that require the percentage of sulfur content as part of the emissions calculation. EIA-767 reports the monthly data on sulfur content in schedule 4. Data are collected from file F767_Boiler_Fuel, reported to the nearest 0.01 percent. I take the weighted average from the monthly data as an average percentage of annual sulfur content for each boiler. For observations with missing values on sulfur content, industry weighted average level of sulfur content is applied.

- FGD sulfur dioxide efficiency

  The reported efficiency of the plant's FGD units is used to convert the uncontrolled to controlled emission estimates. EIA-767 reports FGD sulfur dioxide efficiency in schedule 8, line 6. The data are collected from file F767_FGD, column I, which is reported to the nearest 0.1 percent after adjustment of annual operating time for each plant. For plants that did not report in EIA-767, the uncontrolled emission level is produced.

C. Estimate NO_X emissions:

Following EIA *Electric Power Annual*, NO_X emissions are estimated as:

$$\begin{aligned} NO_X\ emissions(tons) &= fuel\ consumption\ (tons\ for\ solids, barrels\ for\ liquids, \\ &\quad thousand\ cubic\ feet\ for\ gases) \\ &\quad \times emission\ factor(pounds\ per\ ton, barrel, or\ Mcf) \\ &\quad \times (1 - reduction\ percentage) \times \frac{tons}{pound} \end{aligned} \tag{A.3}$$

- Fuel consumption

  Data on fuel consumption are the same as in the calculation of SO_2 emissions, taken from Form EIA-920/906, column of "year-to-date electric fuel consumption quantity."

- Combustion system type

  I follow the same method as in the above discussion of estimating SO_2 emissions to obtain information on combustion system type. In addition, the boiler design of wet- or dry-bottom is collected from EIA-767, file F767_boiler. Firms that did not report in EIA-767 are assumed to have dry-bottom boiler design.

- Emission factor

  Emission factors for nitrogen oxides are reported in Table A1, EIA *Electric Power Annual* (2003) and Table A2 *Electric Power Annual* (2006), based on the information on fuel type, combustion system and boiler design of wet-bottom or dry-bottom. Similarly to the estimation of SO_2 emissions, I obtain the emission factors, and match them with fuel consumption information with proper unit conversion.

- NO_X control process

  The types of NO_X control process are reported in EIA767, file F767_boiler. Up to three types of control process are reported for each boiler, based on predominance.

- Reduction percentage

  Table A3 in EIA *Electric Power Annual* (2003) provides the reduction percentages for each type of controlling process, and for boilers with multiple control systems that have combined controlling effects. After applying the reduction percentages, the uncontrolled emissions are then converted into controlled level of emissions.

In summary, the emission variables constructed in this study include CO_2 emissions, estimated as the uncontrolled level, and SO_2 and NO_X emissions, as the controlled level after adjusting for emission abatement technology. For the plants that did not report on the historic Form EIA-767, data on pollution control equipments are unavailable and the uncontrolled estimates are not reduced.

A.2 Firm production data

The data used in this study are an updated and refined version of the dataset by Atkinson and Honerkamp, which is also consistent with Nelson (1984). I update the dataset to include more recent years, especially the late 1990s, when the cap-and-trade system was established for SO_2 and NO_X emission. The firm production data are collected from Federal Energy Regulatory Commission (FERC) Form-1.

A. Input data:

Inputs data include expenditures and prices on capital, labor and energy. The methods on computing input data follow Christensen and Jorgenson (1996), and Atkinson, Cornwell and Honerkamp (2003).

- Capital

  The price of capital is defined as the product of the yield on the firm's latest issue of long-term debt and the Handy-Whitman index for electric utility construction costs. For bond yield, as utilities did not issue long-term debt very often, to avoid the data being sparse, I find the bond rating of the utility's most recently issued long-term bonds, then take the average yield with corresponding rating. Bond ratings and annual average bond yield for each rating are taken from Moody's Bond Record and Moody's Public Utility Manual. The Handy-Whitman Index for electronic utilities construction costs is used to adjust the price of capital. The index is taken from Moody's Public Utility Manual (2003) and Statistical Yearbook of the Electric Utility Industry (2005), "Cost Trends of Electric Light and Power Construction."

Expenditure on capital (EXPK, in 10,000 dollars) is defined as:

$$\begin{aligned} EXPK &= \left(\frac{long\ term\ interest\ payment}{capital\ LTD\ ratio} + depreciation\ expenses\right) \\ &\times \frac{asset\ of\ total\ steam\ plant}{asset\ of\ net\ total\ utility\ plant} \times \frac{1}{10000} \end{aligned} \tag{A.4}$$

- Labor

The price of labor (PL, in dollars per worker) is calculated as total salaries and wages charged to electric operation and maintenance, divided by the sum of the number of full-time and one-half the number of part-time employees. Information on the number of full-time and part-time employees is collected from FERC form-1 until 2001. Since 2002, as this form stopped reporting information on the number of employees, I instead use the total number of employees in firms' income statements from Mergent (formerly known as Moody's) and COMPUSTAT. Expenditure on labor (EXPL, in 10,000 dollars) is computed as the sum of salaries and wages charged to the electric production account multiplied by the ratio of steam to total net electricity generation. Therefore, quantity of labor (QL) is obtained by dividing expenditure on labor by price of labor.

- Energy

Expenditure on energy (EXPE, in 10,000 dollars) is collected from FERC form-1, Electric Operation and Maintenance Expenses, on fuel expenditures. Quantity of fuel consumption (QE, in MMBtu) is calculated from EIA form-906/920. Prior to 2001, fuel consumption at the plant level is reported in physical units in EIA form-920, fuel quality and heat content information is taken from FERC-423 to convert fuel consumption into million Btu (MMBtu). Since 2001, fuel consumption in MMBtu is directly taken from EIA form-920.

B. Output data:

Output data on sales and revenues are collected from FERC form-1, Sales of Electric Operating Revenues. They include sales to residential, commercial, industrial, wholesale

(SALR, SALC, SALI, QW, in 10,000 kilowatt hours) and revenues on electricity sales (REVR, REVC, REVI, REVW, in 10,000 dollars). Firm-level steam generation of electricity, STMQ (in 10,000 kilowatt), and net generation of electricity, NETQ (in 10,000 kilowatt) are also collected from FERC form-1, Electric Energy Account. QOTH is defined as the difference between NETQ and STMQ to control for the electricity generated by other methods, such as nuclear and hydro power.

C. Firm vintage index:

Firm vintage index measures the age of the firms' steam electric-generating equipment. Data on firm vintage are updated from the original data set till 2005. Following Nelson (1984), the vintage index is computed as a weighted average of the age of each firm's steam-generating equipment, where the weights are based on each unit's contribution to total steam-generating capacity. The data required to compute this index include electricity-generating capacity and generating method for each plant in the firms, the year of initial operation, and the year of the last unit installed. They are collected from FERC form-1, steam-electric generating plant statistics (large plants). Nelson pointed out one of the drawbacks of his data on vintage index is that he only used initial installation year to calculate the age, which makes his vintage index overstate the true average ages. I modified this methodology by including the year of last unit installed, and taking the average of the year of initial operation and the year of the last unit installed as the age. Therefore, if an additional unit was installed after initial operation, vintage index is computed as

$$vintage = \frac{capacity_1 \times \frac{initial\ \ year_1 + last\ \ unit\ \ year_1}{2} + capacity_2 \times \frac{initial\ \ year_2 + last\ \ unit\ \ year_2}{2} + ...}{capacity_1 + capacity_2 + ...} \tag{A.5}$$

For the situation where an additional unit was installed after 1998, I separate the information on original and additional capacity as the corresponding weights to compute the overall age. To keep close consistency with the original data on vintage index while correcting part of the data bias pointed out by Nelson (1984), I use the incremental change computed by my modified equation (A.5) to update the original vintage index from 1998–2005.

A.3 Events of merger & acquisitions and divesting activities

Table A.1: Merger Acquisitions and Divesting Activities

	Firm Name	FIRMID	M&A Activities	Post M&A Data Availability
1	Central Illinois Public Service Co.	3253	Merged with Union Electric, became subsidiary of Ameren Corp.	Yes
2	Baltimore Gas & Electric Co.	1167	Holding company:Constellation Energy Group	No
3	Boston Edison Co.	1998	Sold generating assets to Sithe Energies, a subsidiary of Dynergy	No
4	Central Hudson Gas & Electric Corp	3249	Form CH Energy Group	No
5	Central Maine Power	3266	Merged to CMP group, then merged with East Energy	No
6	Central Power and Light	3278	Became subsidiary of American Electric Power	Yes
7	Cincinnati Gas & Electric	3542	Merged with PSI resources, formed CINergy	No
8	Central Louisiana Electric Co.	3265	Merged with Cleco	No
9	Common Wealth Edison	4110	Sold generating assets to Edison Mission Company	No
10	Delmarva Power and Light	5027	Merged with Atlantic Energy, formed Conectiv, later acquired by Pepco	No

	Firm Name	FIRMID	M&A Activities	Post M&A Data Availability
11	Duquesne Light Co.	5487	Sold generating assets to Orion Power Midwest	No
12	Houston Lighting and Power	8901	Merged with Houston Industries, renamed to HI, then Reliant Energy, then Center Power Energy Houston Electric.	No
13	Illinois Power Co	9208	Sold generating assets to Illinova, then Dynergy generation, last sold to Ameren	No
14	Interstate Power Co.	9392	Merged with Interstate Power and Light, name change.	Yes
15	Long Island Lighting Co.	11172	Merged with LIPA, formed Keyspan	No
16	Montana Power Co.	12825	Failed. Was bought by Pennsylvania Power and Light	No
17	New England Power Co.	13433	Sold generating assets to Pacific Gas & Electric Corp	No
18	New York State Electric and Gas Co.	13511	Reincorporated in 1998	No
19	Niagara Mohawk Power Corp	13573	Plants acquired by NRG Energy in 1999, PSEG purchased steam plant in 2000	Yes

	Firm Name	FIRMID	M&A Activities	Post M&A Data Availability
20	PECO Energy Co.	14940	Merged with Unicom, who owns Commonwealth Edison, and formed Exelon Corp. in 2000	No
21	Pennsylvania Power & Light Co.	14715	Fuel oil leaking from power plants, considered as hazard wastes. Sold assets to Sunbury Holdings, LLC	No
22	Potomac Edison Co.	15263	Transferred its generation assets to Allegheny Generating Co to Allegheny Energy Supply	Yes
23	Potomac Electric Power Co.	15270	Sold generation assets to Southern Energy	No
24	Public Service Electric and Gas Co.	15477	PSE&G was split into PSE&G, a regulated gas and electric delivery company in New Jersey and PSEG Power, an unregulated US power generation company	Yes
25	San Diego Gas and Electric Co.	16609	Sold power plants to Dynergy, NRG Energy	No
26	Texas Utilities Electric Co.	44372	Missing values after deregulation since 2002	No

	Firm Name	FIRMID	M&A Activities	Post M&A Data Availability
27	United Illuminating Co.	19497	Sold generation assets and divested from generation projects, became subsidiary of UIL holding corp in 2000	No
28	West Penn Power Co.	20387	In 1999, Co. transferred its 45% ownership in AGC to Allegheny Energy Supply at book value	Yes

A.4 Utility code change

The following utilities changed their utility code under the EIA reporting system:

1. Montana Dakota Utilities Co. changed from 12819 to 12911.
2. Pennsylvania Power and Light Co. changed from 14715 to 14716.