Regulatory Effect on Efficiency and Efficiency Measurements of Power Generating Companies: A Data Envelopment Analysis (DEA) Application

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1. Introduction

Electricity is one of the major inputs in the production and service industries. Especially increasing portion of the service industry in the U.S. economy last two decades, the importance of quality in electric generation, transmission and distribution has increased substantially. Since electricity cannot be stored economically, it is necessary to satisfy the electric power demand at all times. Therefore, electric must be generated in the most efficient way to receive more reliable and cheaper for a growing economy.

The deregulation (restructuring) of the electric power industry forces the companies to produce more electricity for less in order to survive in the competitive market. Even in a non-competitive environment, productivity and efficiency are important because of scarce resources. Energy Policy Act of 1992 (EPAct) is only the beginning of the competitive market for electricity in the U.S. Deregulation and restructuring will continue until the electricity price is reduced to a reasonable level. In a competitive market, price of electricity is set by the market; thus, the utility companies have to reduce cost to compete with the other electric utility companies. The most effective way to reduce cost is using the resources more efficient while producing more. Therefore, efficiency is a very vital concept for the power generating companies, state and federal governments to provide electricity to the end-users for less, and crucial to the framing of appropriate and effective national energy policy. Restructuring is a term that reflects the regulatory changes from a natural monopoly to a competitive market by unbundling the genaration, transmission and distribution of functions. Not all states in the U.S. have intended to apply restructuring in the first place. The leading restructuring states are generally the states with high electricity prices. As of 2000, 24 states have passed legislation or ordered restructuring (EIA, 2000). New York has joined these states by regulating retail sales operations.

This paper studies the efficiency performances of 74 U.S. electric power companies for the period 1986-2000. Empirical results were obtained by using DEA technique with two DEA models: CCR and and BCC models in order to measure the efficiencies of electric power companies . By using test statistics, we compare the efficiency results between regulated and deregulated time periods (cross-time); and the electric utility companies which operates in a states pass the deregulation laws and the ones which are still regulated (cross-state). The time frame that we cover in this study consists of both regulated and deregulated era of the U.S. electric power industry. Therefore, we had a chance to see if any efficiency differences during these periods.

The efficiency of power companies can be performed in two ways: company level and plant level. Diewert and Nakamura's (1999) study examines 77 power plants in 28 countries which are funded by the World Bank. The main findings of the study are that the average efficiency increases when the size of the plant increases private companies are more efficient than public companies. Bagdadioglu et al. (1996) also reached the same conclusion with measuring the technical efficiencies in the Turkish electricity distribution industry that franchised (private) organizations have higher scale efficiency than public-owned distribution organizations, but, there is no significant difference of overall technical and pure technical efficiency between the 10 distribution organizations. The most efficient public utilities will most likely be privatized first. In our paper, the U.S. electric power (utility) companies were chosen as large Investor-Owned-Utilities, which are known as private companies. Therefore, we do not have any distinction such as public and private, but, we examine efficiency differences between the states which deregulated the electric power industry and the states which are still regulated.

Efficiency improvements in power companies may be possible by either using less inputs, such as capital, labor and fuel or increasing outputs by using more advanced technologies. New Technologies can be obtained either from outsourcing or from Research & Developmentment (R&D) departments in the company. We used a similar procedure with Connolly (1997) in order to measure efficiency, but, the scope in our paper is measuring the technical efficiency performances of electric utility companies and investigating the deregulation effect on efficiency. Therefore, we have some input differences, comparing with Connolly's study (R&D expenditures, nuclear ratio, etc). Besides total factor productivity (TFP) measurement, Connolly used the DEA technique to measure the efficiency of electric power companies which are assumed to have constant returns to scale and variable returns to scale in order to investigate if there is a relationship between efficiency and Research & Development (R&D). This study shows that there is no significant relationship between R&D expenditures and efficiency in the electric power industry. Chitkara's (1999) study contradicts Connolly's findings as the productivity and efficiency increase in the power plants because of an increase in new technological knowledge, improved managerial practice, learning by doing, and better use of inputs. We agree on Chitkara's conclusion, but, the real impact of improving efficiency comes from the better use of inputs. Also, there are still big debates on measuring effect of technology, knowledge and learning. Therefore, our research scope in this paper is shaped as increasing efficiencies of power generating companies by reducing the input used in the electricity generation.

The plan of the paper is as follows. Second section, following the introduction, gives information about data collection procedure: Input and output variables for the Data Envelopment Analysis (DEA), and regulatory variables for the regulatory environment rankings report of Duff & Phelps, Inc and the Retail Energy Deregulation Markets (RED) Index published by the Center for the Advancement of Energy Markets (CAEM) in order to determine the deregulation level for a particular state. Third section explains the DEA methodology used in the paper. Fourth comes with empirical results, comparing in terms of small and large utility companies, and utility companies operating in regulated and deregulated states. Finally, it concludes.

2. Data Collection

The data, which are used in this study can be collected in two parts: first one is the input and output variables for DEA models; the second is the deregulation level of a particular state in order to establish a competitive electric power market.

2.1. DEA Variables:

In DEA technique, we have to define the inputs, which are necesseary for electric generation, and outputs, which are the final product (megawatthour electricity generation) per customer type (residential, commercial, industrial, and other).

The input variables in this study are capital (net utility plant), labor (number of employees in electric generation units), quantity of fuel, and quantity of materials. Capital cost is the depreciation expense which represents the value of total depreciation expense of plants used. Interest charges and paid dividends are included to depreciation expense in this study. Labor is the number of employees worked in electric generating division (Part-time employees are considered working as 20 hours a week; therefore, we have to adjust the total number of employees as full-time employees plus half of part-time employees). Fuel is the purchased fuel used to generate electricity prices. Another variable is other expenditures including purchased services and materials, and other related items in the production system.

In order to calculate quantity of fuel, we used price of fuel obtained from Bureau of Labor Statistics (BLS) of the U.S. Department of Labor as producer power index (PPI) under the section of fuel and related products and power in annual values (BLS,2003). Price of materials (other expenditures) is derived from the input-output accounts table in the BLS of the U.S. Department of Labor, and Bureau of Economic Analysis (BEA) of Department of Commerce. The input-output (I-O) accounts show how the industries provide input to and use output from other industries (BEA,2003).

The output variables are collected into two parts: In the first approach , aggregated output was computed and used as a single output variable. In the second approach, the output variables are separated to megawatt hours (MWh) sold to the residential, commercial, industrial and other consumers. Initially, it is expected that the multiple output model should give more efficient units than the single model because some DMUs may rely heavily on some individual outputs.

The inputs (capital, labor, fuel, and material expenditure) and outputs (megawatt hours (MWh) sold to the residential, commercial, industrial and other consumers) are obtained from FERC Form 1 Survey. Federal Energy Regulatory Commission's (FERC) Survey Form 1, called "Annual Report of Major Electric Utilities, Licensees and Others." includes financial reports, such as comparative balance sheet, statement of income, statement of retained earnings and statement of cash flows; and electric generation and transmission data for the particular year, such as distribution of salaries and wages, number of electric department employees, megawatt hour generation by sources (steam, nuclear, hydro and other), and megawatt-hours sold to the consumers (residential, commercial, industrial, and other). The utility companies have to file the survey Form-1 to the FERC every year, and the FERC makes it available in a open-to-public-database. To download the database, the researcher must install a software from the FERC website (www.ferc.gov.tr).

2.2. Regulatory Effect Variables

The deregulation (restructuring) in the U.S. is still under serious consideration. The states with higher electricity price have accepted the restructuring of the electric power industry, but, the remaining states have not. The main argument of the states, which regulate electric power industry is that there is no need to change the system because the electricity is cheap to the end-user. Goto and Tsutsui (1998)'s study compares the Japanese and U.S. electric utilities in terms of overall cost and technical efficiencies. They found the Japanese utilities were more efficient than the US utilities in terms of cost, technical, allocative and scale efficiencies in the period of 1984-1993. The authors suggest that creating a free market in Japan might reduce the electricity prices. In our article, we investigate if there is any efficiency performance differences between the U.S. utility companies in states, which regulate the market, and the ones, which are deregulated.

We use two reports in order to measure the regulatory effects of state commissions on efficiency of power generating companies. The first is the State Regulatory Environment Ranking, published by Regulatory Developments Public Utility research Division of Duff & Phelps, Inc.; and the second is the Retail Energy Deregulation (RED) Index, published by Center for Advancement of the Energy Markets.

The regulatory environment rankings report of Duff & Phelps, Inc. is published to measure the "friendliness" of the state public regulatory commissions to the end-users. A successful state commission is measured with the tightness to the utility company in limiting the firm's rate of return to its cost capital (Nelson and Wohar, 1983).

The rankings on this report are collected in five levels; "I" is the most, and "V" is the least friendly. The company used six levels instead of five before 1990; therefore, all rankings are adjusted to five levels. The available data of state regulatory ranking are until 1991; thus, our analysis regarding regulatory ranking in a regulated industry has a gap between 1992 and 1996. However, we do not see any disadvantages of unavailability because the state legislators do not change very fast, and six years data should be giving us a good idea of behavior of the state regulatory commissions to the end-users and the utility companies. The rankings of states have been determined in terms of normalized versus flow-through accounting of book-tax timing differences, use of more up-to-date or prospective test periods and rate bases, inclusion of construction work in progress in rate base in operating income, granting of interim rates within a relatively short time, minimal delay in issuing final decisions to reduce regulatory lag, allowing reasonable rates of return, and permitting comprehensive automatic adjustment clauses or other expedited fuel cost recovery procedures. The report also covers the political and economic factors with regulatory responses such as long or short term phase-ins, excess capacity penalties, and/or disallowed plant costs. The final score reflects whether the utility companies earned a decent rate of return, a good earnings quality and a reasonable equity ratio in a period when the utility needs regulatory support (Duff & Phelps Inc, 1986-1991).

The second regulatory study is conducted by the Center for the Advancement of the Energy Markets (CAEM). The CAEM provides information, and publishes the RED Index in order to measure the restructuring efforts in the U.S., Canada, portion of Australia and the United Kingdom. The RED Index is a scorecard which measures the progress on energy restructuring. The main determinants of the scorecard are public policy, customer conditions, and the size and density of the market. The index starts in 1997, but, most of the states are scored zero in that year because there were not many attempts on restructuring in the beginning. Every year new states passed the deregulation law, and we see significant differences in every issue of the report.

The RED Index gives the scores only if there is an effort on deregulation, it does not give any provisional credits for future actions. Another point we should mention about the index scoring is that a high score does not mean the restructuring has reached its goals of reliable and cheap electric power in a particular state; however, it shows the states has passed the laws on deregulation, and started the restructuring. The difference in scores comes from the choices of application in restructuring. The expectations from the restructuring are providing reliable, environmentally friendly, less costly energy to the end-users.

The RED Index collects the scores in twenty-two attributes under five clusters; competitive framework, generation, consumer, distribution, and commission (Table 1). Total weights are accounted to one hundred. Each attribute has its own survey questions measuring how the state established a good market structure in order to increase restructuring (CAEM, 2002).

Table 1. RED Index Attribute Description and Scoring Weights, and Major Questions

Attribute	Description	Wt.	Question
COMPETITIVE FRAMEWORK CLUSTER			
Attribute 1	Deregulation Plan	5%	Does a detailed restructuring plan exist?
Attribute 2	Percent of Eligible Customers	5%	What percentage of customers are eligible for retail access?
Attribute 3	Percent Switching	5%	What percentage of retail customers have switched to a nonutility supplier?
Attribute 4	Competitive Safeguard	10%	What safeguards prevent affiliate favoritism by utilities?
Attribute 5	Uniform Business Practices	10%	To what degree are business practices standardized?
Attribute 6	Competitive Billing	3%	Is retail customer billing a competitive service?
Attribute 7	Competitive Metering	2%	Is retail customer metering a competitive service?
GENERATION CLUSTER			
Attribute 8	Generation Market Structure	10%	What is the market structure for generation?
Attribute 9	Wholesale Market Structure	10%	How centrally controlled is the wholesale market?
Attribute 10	Stranded Cost Calculation	3%	Do stranded costs meet a market test?
Attribute 11	Stranded Cost Implementation	3%	Are stranded cost charges fixed?
CONSUMER CLUSTER			
Attribute 12	Customer Information	2%	Are supplier granted effective access to customer information?
Attribute 13	Consumer Education	2%	Is a comprehensive consumer education program required?
Attribute 14	Default Provider Price	10%	How are default customers handled?
DISTRIBUTION CLUSTER			
Attribute 15	Default Provider Price Risk	4%	Do default prices allow effective competition from supplier?
Attribute 16	Default Provider Rates	4%	Are default rates properly set?
Attribute 17	Performance-Based Regulation for Network Facilities	2%	Is performance-based pricing used for network facilities?
Attribute 18	Network Pricing	2%	Are efficient pricing principles used for network pricing?
Attribute 19	Interconnection to Grid	5%	Do policies allow small-scale generation?
COMMISSION CLUSTER			
Attribute 20	Regulatory Convergence	1%	Are retail gas and electric policies integrated?
Attribute 21	Commission Reengineering	1%	Has the commission reengineered its processes for a new regulatory regime?
Attribute 22	Commission Budget	1%	Is the commission's budget commensurate with its new responsibilities?

(Source: CAEM, 2002)

3. Methodology

DEA is a non-parametric optimization technique which measures the efficiency of the decision making units (DMUs) by using linear programming methodology. A DMU is an entity, which we measure the efficiency levels, to be compared with other entities in the population. In our case, a DMU is identified as an electric power generating company for a particular year, for example Alabama Power Company in 1986 is concidered as a DMU and in 1987 is another DMU. We measure the efficiency level of a company in a particular year (called DMU), and show which input must be reduce to reach the efficient company level.

Unlike the conventional parametric techniques, it does not look at the averages of the dataset. Instead, DEA sees each DMU as a separate entity, which has to be compared to the others before setting the final efficiency level. DEA reduces the error term in the estimation function. The differences between DEA and parametric techniques can be seen more clear in Figure 1.

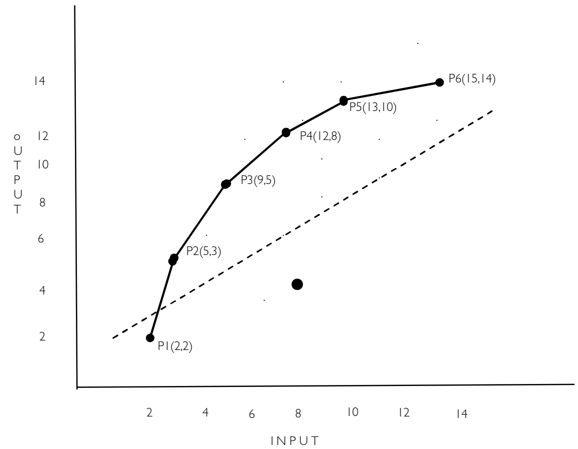

Figure 1. Comparison of DEA and Regression

When DEA performes the efficiency analysis, it sees the decision making units (DMUs) as whole. It calculates the inefficiencies by comparing the inputs and outputs of efficient units on the frontier line. This line is also called best practice efficient frontier line. it can be seen as the concave line between P1 and P6 in Figure 1.

Technological change may affect the efficiency of power companies. In this study, technology of generation is recognized as hydro, nuclear and fossil fuel generation types, and technology in distribution includes the mix of residential, commercial, industrial and "other" customer categories. Since this paper focuses on the overall efficiency of the electric power companies, some technological differences among the utility companies are not considered. However, greater technological detail could be considered in a plant level analysis.

In this study, the CCR and the BCC models are used to measure overall (relative) technical efficiency with constant returns to scale (CRS) and variable returns to scale (VRS) possibilities in the envelopment surface. "Relative technical efficiency is calculated by forming the ratio of a weighted sum of outputs to a weighted sum of inputs, where the weights for both outputs and inputs are to be selected in a manner that calculates the Pareto efficiency measure of each DMU subject to the constraint that no DMU can have a relative efficiency score greater than unity; and the relative efficiency of each DMU is calculated in relation to all the other DMUs, using the actual observed values for the outputs and inputs of each DMU " (Charnes et al., 1994). Pure technical efficiency can also be calculated by decomposing the overall technical efficiency (eliminating the scale efficiency), but it is out of our scope in this study (Bagdadioglu, 1996).

Both models are able to do the analysis focusing on either an input or output perspective. In an input oriented DEA model, the objective is moving through the frontier line by reducing the inputs while the output level remains the same; on the other hand, in an output oriented model, the focus is proportional increase in output while the input level remains the same.

DEA sees the population as a whole, and makes the comparison between decision making units (DMUs). DEA draws the piecewise efficiency frontier line to determine efficient DMUs. The DMUs on the line are considered efficient; otherwise, are inefficient. Since we use an input oriented approach, we are looking for proportional decrease in the input mix (capital, labor, fuel, and other materials), while producing the same amount of output (megawatt-hour generation electricity).

In Figure 2, the straigth line, starting at the origin represents the CCR model; and the concave line represents the BCC model. If we pick an electric utility company (DMU O2), the utility company generates QA amount of electricity, while using XA' amount of inputs (capital, labor, fuel, and other materials) for a particular year. Apparently, the utility company (DMU O2) is not efficient because it is not on the line. It has to use XA amount of inputs according to the BCC, and XA* amount of inputs according to the CCR model. Connolly (1997) suggests using the BCC model in measuring efficiency of electric power companies. However, we will use both models in order to introduce different aspects of efficiency measures.

The DEA technique requires a systematic procedure that a researcher must follow. This procedure includes defining the population, setting the goals, selecting Decision Making Units (DMUs), formulazing initial model and testing, formulizing final model, analyze by factor, general conclusions and analyzing with individual DMU (Golany and Roll, 1989), and Golany Roll, and Rybak (1994) applied the same procedure in the electric power industry in Israel. In our study, the population is the U.S. investor-owned-utilities; the goals are measuring efficiencies of power companies and examining if deregulation of the U.S. power market has a positive effect on efficiency; DMUs are the U.S. Investor-Owned-Utility Companies from 1986-2000. We tested our model with different input-output selections, and then finalized the model for the CCR and BCC models. We conclude with the analysis of the results.

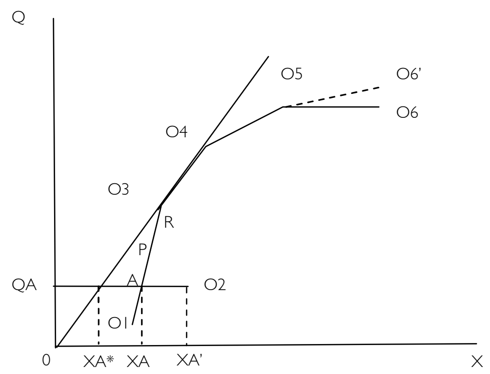

Figure 2. Envelopment Surfaces for the CCR and the BCC Input Oriented Models

3.1. CCR Input Oriented Model

The CCR model was introduced by Charnes, Cooper, and Rhode's in 1978 (Charnes et al., 1994). The model was named after the first initials of the introducers. This method draws the envelopment surface with a constant returns to scale approach in a straight frontier line (like a simple linear regression line). The CCR model's frontier line starts at the origin, and the DMUs on this line are considered as efficient units (Figure 2). In an input oriented CCR model, the inefficiencies of DMUs can be eliminated by a proportional decrease in the input mix, while producing the same amount of output. The input mix in our study is capital, labor, fuel, and other (material). The CCR model finds the inefficient units, comparing with the efficient utility company output and inputs, then making recommendations how much each input must be reduce in order to generate same amount of electricity. The CCR Input oriented model can be described as follows;

$$\min_{\theta,\lambda,s^+,s^-} z_0 = \theta - \varepsilon\left(\sum_{r\in O_D} s_r^+ + \sum_{i\in I_D} s_i^-\right) \qquad (1)$$

$$s.t.\ \theta X_{io} - \sum_j X_{ij}\lambda_j - s_i^- = 0$$

$$\sum_j Y_r\lambda_j - s_r^+ = Y_r$$

$$\lambda_n \geq 0 \ s_r^+ \geq 0 \ s_i^- \geq 0$$

,where

z_0 = the efficiency rating that measures the distance from the efficient frontier line

θ = proportional reduction applied to all inputs of DMU to improve efficiency

ε = a very small number which allows the minimization over θ, involving the slacks

O_D = discretionary (desired) outputs,

I_D = discretionary (desired) inputs,

X_{io}= Input vector of a designated DMU for a particular input type (Capital, labor, fuel, and other)

X_{ij} = Input vector of DMU in a given year for a particular input type (Capital, labor, fuel, and other)

Y_r = Output vector of DMU

r = index for the outputs, Megawatthours sold to the type of customers (Residential, Commercial, Industrial, and Other).

i = index for the inputs, i = Capital, Labor, Fuel, and Other

j = index for DMUs in a given year,

o = designates the analyzed DMU,

λ_j = coefficients associated with the selection of an efficient frontier point for the evaluation of DMU_O,

s_r and s_i are slack variables for the outputs and inputs respectively,

The model calculates the optimal efficiency level as a minimum value of the objective function. In an input oriented model, the slack variables are the necessary input reduction (capital, labor, fuel, and other material) to improve efficiency of efficient companies (DMUs). The first constraint indicates that the efficiency of a DMU equals the sum of amount of input reduction (slack variable) and amount of input (X) used by efficient companies. The second constraint indicates that the output level of an inefficient company must be equal to the difference between the output level of an efficient company and slack variable of output. There are two output mixes used for this method; one is the aggregated output, which the sales of megawatt hours to the customer are weighted with the revenues from the customer types; residential, commercial, industrial, and other (CCR). Second is the disaggregated output by customer category, megawatt-hour (MWh) sold to the residential, commercial, industrial, and other consumers (CCR4). The difference between CCR and CCR4 models is that there are 4 outputs in CCR4 model where as only one output in CCR model.

A DMU is considered to be efficient if and only if θ is 1 and slack variables are zero. Any nonzero slack variable corresponds to the inefficiency level to the frontier line. It shows that the efficiency improvement can be achieved by the reduction of the number of input units from the production system in an input oriented case as used in this study.

3.2. The BCC Input Oriented Model

The BCC model has a similar idea with CCR model. The only difference is that the frontier line (shape of envelopment surface) is not a straight line like in the CCR model (Figure 2).

Therefore, we recall the descriptions of the objective function and constraints from the CCR model. Since the BCC model has a conical hull frontier line, it covers more DMUs than the CCR model does (Figure 2). The BCC input-oriented model primal formula can be shown as

$$\min_{\theta,\lambda,s^+,s^-} z_0 = \theta - \varepsilon\left(\sum_{r\in O_D} S_r^+ + \sum_{i\in I_D} S_i^-\right) \tag{2}$$

$$s.t.\theta X_{io} - \sum_j X_{ij}\lambda_j - s_i^- = 0$$

$$\sum_j Y_r\lambda_j - s_r^+ = Y_r$$

$$\sum_j \lambda_j \geq 1$$

$$\lambda_n \geq 0 \; s_r^+ \geq 0 \; s_i^- \geq 0$$

,where

z_0 = the efficiency rating that measures the distance from the efficient frontier line

θ = proportional reduction applied to all inputs of DMU to improve efficiency

ε = a very small number which allows the minimization over θ, involving the slacks

O_D = discretionary (desired) outputs,

I_D = discretionary (desired) inputs,

X_{io} = Input vector of a designated DMU for a particular input type (Capital, labor, fuel, and other)

X_{ij} = Input vector of DMU in a given year for a particular input type (Capital, labor, fuel, and other)

Y_r = Output vector of DMU

r = index for the outputs, Megawatthours sold to the type of customers (Residential, Commercial, Industrial, and Other).

i = index for the inputs, i = Capital, Labor, Fuel, and Other

j = index for DMUs in a given year,

o = designates the analyzed DMU,

λ_j = coefficients associated with the selection of an efficient frontier point for the evaluation of DMUo,

s_r and s_i are slack variables for the outputs and inputs respectively, A DMU is considered to be efficient in the BCC model if and only if

1. $\theta = 1$, and

2. all the slack variables are zero.

The optimal efficiency level can be achieved by two ways; one is reducing the number of units from the production system (increasing θ); and the other, reducing the amount of input slacks to improve the efficiency level or decrease the inefficiency of the DMU, it is same as the CCR model.

The growth of the DEA efficiency level of each DMU is calculated as the natural log differences between time t and time t-1 of CCR and BCC values; DCCR and DBCC, respectively. The value shows how much growth was achieved between time periods.

4. Empirical Results

In this paper, we used two DEA models in order to measure efficiencies of electric power companies; CCR and BCC models. In both models we used the same variables: input variables are capital, labor, fuel , and other materials; and output variable is the megawatt-hour electricity sold to the customers. In CCR4 and BCC4 models, we disaggregated the output to 4 outputs (megawatt-hour electricity sold to the residential, commercial, industrial and other customers).

We would like to recall the model definitions before introducing empirical results.

CCR: The efficiency level of a DMU (a company) by using CCR model with one output (Total-aggregated megawatt- hours sold to the end users).

CCR4: The efficiency level of a DMU (a company) by using CCR model with 4 outputs (megawatt-hours sold to the residential, commercial, industrial and other end users).

BCC: The efficiency level of a DMU (a company) by using BCC model with one output (Total-aggregated megawatt- hours sold to the end users).

BCC4: The efficiency level of a DMU (a company) by using BCC model with 4 outputs (megawatt-hours sold to the residential, commercial, industrial and other end users).

DCCR: The growth rate of efficiency level of DMU (company), measured by CCR model with one output (Total-aggregated megawatt- hours sold to the end users).

DCCR4: The growth rate of efficiency level of DMU (company), measured by CCR model with 4 outputs (megawatt-hours sold to the residential, commercial, industrial and other end users).

DBCC: The growth rate of efficiency level of DMU (company), measured by BCC model with one output (Total-aggregated megawatt- hours sold to the end users).

DBCC4: The growth rate of efficiency level of DMU (company), measured by CCR model with 4 outputs (megawatt-hours sold to the residential, commercial, industrial and other end users).

We used IDEAS software to solve the constrained optimization problems describing our model. IDEAS has three basic steps to perform the DEA analysis: The first step is the entering input output data in a spreadsheet; The second step is that selecting the model (CCR, BCC etc) type and orientation (input or output). In the last stage, the analysis is performed, and the results are obtained. Since the DEA measures efficiencies of DMUs by comparing each indivudual DMU (company), we had to run the program separately for each time period (1986-1990, 1991-1995 and 1996-2000). The number of DMUs, number of efficient units and average iteration in solving the problem is shown in Table 2.

Table 2. General Statistics of Performing DEA Models

Periods	DEA Model	Number of DMUs Solved	Number of Efficient DMUs	Average Number of Iterations
1986-1990	CCR	370	19	11
	CCR4	370	48	21
	BCC	370	48	15
	BCC4	370	93	29
1991-1995	CCR	365	25	11
	CCR4	365	56	26
	BCC	365	50	16
	BCC4	365	115	41
1996-2000	CCR	330	27	8
	CCR4	330	54	18
	BCC	330	50	15
	BCC4	330	106	32

The number of DMUs changes from period to period because of missing data points for some utility companies. As we mentioned earlier, the models with four outputs (CCR4 and BCC4) almost double the efficient number of companies, comparing with the models with one output models (CCR and BCC); respectively. The reason is that some utility companies might focus on some individual customers (residential, commercial, industrial and other). The number of iteration increases when the number of input and output increase.

We reached the feasible solutions while running the program. Z-value in the objective function represents the efficiency level of a particular DMU. In the emprical results section of our paper, we denotes it as CCR, CCR4, BCC and BCC4. The slack variables are the necessary input reduction for a DMU in order to reach an efficient company as shown in Table 9.

4.1. The DEA Results

Descriptive statistics of DEA scores are shown in Table 3. Because of the model differences and output variable differences between single and multiple output sets, the means of the efficiency scores and the growths are different. Kurtosis and skewness values are away from the normal distribution assumptions. The differences of CCR and CCR4 or BCC and BCC4 models are based on the output selection. The CCR and the BCC models have a single output variable of aggregated output; on the other hand, the CCR4 and the BCC4 models have four outputs; MWh sold to the residential, commercial, industrial, and other consumers.

Table 3. Descriptive Statistics of DEA Results

	Mean	Std. Dev.	Kurtosis	Skewness
CCR	0.7138	0.1679	-0.8233	-0.0568
CCR4	0.7964	0.1575	-0.9770	-0.3221
BCC	0.7892	0.1672	-0.7306	-0.5076
BCC4	0.8698	0.1452	0.0480	-1.0479
DCCR	0.0129	0.1006	21.1642	0.2058
DCCR4	0.0114	0.0881	8.9795	0.9154
DBCC	0.0103	0.0938	8.9200	1.0282
DBCC4	0.0082	0.0830	9.8075	0.8489

Table 4 shows the 15 years averages of the DEA scores and growth rates. According to the DEA Scores, Idaho Power, Kentucky Power, Kentucky Utilities, Entergy New Orleans, and Puget Sound have the best DEA scores in 15 year time period. However, Arizona Public Service Company, Consolidated Edison Company of New York, Duquesne Light and KeySpan Generation had the lowest DEA scores in overall.

In the growth of DEA point of view, Commonwealth Edison, Ohio Edison, Orange & Rockland, Pacific Gas & Electric, and the United Illuminating Company have the biggest growth in terms of DEA efficiencies; on the other hand, Bangor Hydro-Electric, Black Hills Power, Cleco Power, the Empire District Electric, Hawaiian Electric, Southern Indiana Gas & Electric, and Wisconsin Power & Light have the lowest DEA growth rates.

Table 5 and Table 6 show the average DEA scores and growth rates, respectively, in three time periods among overall industry, large, and small company perspectives. On average, the DEA scores did not change very much; however, the growth rates in the 1991-1995 period are more less than other two periods. The efficiency scores in the BCC model are higher than the CCR model because of the variable returns to scale assumption and convex hull frontier line. Both DEA models with four output variables score higher than the corresponding single output DEA models.

Table 4. 15-Year-Averages of DEA Scores and Growth Rates

	DEA Scores				DEA Growth Rates			
UTILITY	CCR	CCR4	BCC	BCC4	DCCR	DCCR4	DBCC	DBCC4
Alabama Power Co	0.68	0.72	0.90	0.93	0.0040	-0.0001	0.0083	0.0091
Appalachian Power Company	0.87	0.93	0.97	0.98	0.0010	0.0022	0.0083	0.0079
Arizona Public Service Company	0.47	0.57	0.54	0.69	0.0237	0.0233	0.0242	0.0125
Entergy Arkansas, Inc.	0.65	0.67	0.66	0.68	0.0229	0.0240	0.0219	0.0212
Baltimore Gas and Electric Company	0.66	0.77	0.77	0.92	0.0282	0.0207	0.0218	0.0101
Bangor Hydro-Electric Co	0.75	0.90	0.79	0.92	-0.0023	-0.0078	-0.0096	-0.0088
Black Hills Power, Inc.	0.63	0.69	0.85	0.91	-0.0146	-0.0114	-0.0071	-0.0062
Boston Edison Company	0.51	0.71	0.52	0.83	0.0198	0.0123	0.0224	-0.0063
Carolina Power & Light Company	0.61	0.65	0.80	0.86	0.0172	0.0127	0.0173	0.0119
Central Hudson Gas & Elec Corp	0.52	0.58	0.55	0.61	-0.0028	-0.0053	-0.0051	-0.0088
Central Illinois Light Company	0.78	0.82	0.82	0.85	0.0052	0.0142	0.0049	0.0125
Central Illinois Public Service Company	0.75	0.80	0.76	0.80	0.0374	0.0282	0.0360	0.0280
Cleco Power LLC	0.71	0.83	0.73	0.86	-0.0041	-0.0047	-0.0056	-0.0076
Central Maine Power Company	0.79	0.84	0.82	0.86	0.0202	0.0180	0.0195	0.0180
Central Power and Light Company	0.77	0.83	0.79	0.84	-0.0017	0.0023	-0.0043	0.0024
Central Vermont Public Service Corporation	0.73	0.89	0.80	0.91	0.0176	0.0143	-0.0011	0.0020
Cincinnati Gas & Electric Company, The	0.68	0.78	0.73	0.82	-0.0054	-0.0040	0.0032	0.0011
Citizens Utilities Co	0.70	0.84	0.97	0.98	0.0917	0.0576	0.0027	0.0050
Commonwealth Edison Company	0.55	0.69	0.83	0.99	0.0707	0.0553	0.0532	0.0072
Consolidated Edison Company of New York, Inc.	0.37	0.59	0.45	0.82	0.0081	-0.0040	0.0045	-0.0196
Consumers Energy Company	0.74	0.75	0.83	0.91	0.0042	0.0063	-0.0005	0.0118
The Dayton Power and Light Company	0.65	0.80	0.66	0.82	0.0093	0.0035	0.0095	0.0079
Delmarva Power & Light Company	0.65	0.68	0.66	0.68	0.0161	0.0170	0.0156	0.0183
The Detroit Edison Company	0.60	0.65	0.71	0.84	0.0220	0.0179	0.0143	0.0162
Duke Energy Corporation	0.77	0.78	0.99	0.99	0.0026	0.0042	0.0030	0.0027
Duquesne Light Company	0.51	0.61	0.52	0.66	0.0348	0.0151	0.0337	0.0075
The Empire District Electric Company	0.81	0.91	0.89	0.96	-0.0098	-0.0083	-0.0115	-0.0057
Florida Power Corporation	0.76	0.95	0.83	0.98	0.0172	0.0084	0.0141	0.0102
Florida Power & Light Company	0.80	0.92	0.96	0.98	0.0278	0.0138	0.0083	0.0062
Green Mountain Power Corporation	0.86	1.00	0.97	1.00	0.0270	0.0008	0.0000	0.0000
Gulf Power Company	0.88	0.97	0.89	0.97	0.0021	0.0046	0.0029	0.0043
Hawaiian Electric Company, Inc.	0.61	0.63	0.61	0.64	-0.0396	-0.0320	-0.0396	-0.0329
Reliant Energy HL&P	0.72	0.75	0.90	0.99	-0.0011	0.0036	-0.0051	-0.0056
Idaho Power Company	1.00	1.00	1.00	1.00	0.0000	0.0000	0.0000	0.0000
Illinois Power Company	0.67	0.76	0.71	0.81	0.0122	0.0116	0.0077	0.0078
Indiana Michigan Power Company	0.71	0.76	0.77	0.82	0.0149	0.0136	0.0164	0.0220
Indianapolis Power & Light Company	0.81	0.89	0.82	0.92	-0.0060	0.0024	-0.0069	0.0038
Interstate Power Company	0.81	0.86	0.84	0.90	0.0012	0.0127	-0.0011	0.0076
Kentucky Power Company	0.97	0.99	0.98	1.00	0.0034	0.0026	0.0023	0.0012
Kentucky Utilities Company	0.95	0.98	0.96	0.98	0.0131	0.0083	0.0127	0.0080
KeySpan Generation, LLC	0.45	0.55	0.48	0.59	0.0238	0.0286	0.0264	0.0305
Entergy Louisiana, Inc.	0.92	0.95	0.95	0.98	0.0081	0.0079	0.0110	0.0053
Madison Gas and Electric Company	0.73	0.99	0.81	1.00	0.0093	0.0026	0.0071	0.0014
Maine Public Service Company	0.86	0.94	0.98	0.99	0.0217	0.0009	0.0000	0.0000
Minnesota Power, Inc.	0.90	0.96	0.90	0.96	0.0199	0.0241	0.0179	0.0212
Entergy Mississippi, Inc.	0.85	0.89	0.91	0.94	0.0324	0.0211	0.0386	0.0223
Montana Power Company, The	0.90	0.96	0.92	0.96	0.0000	0.0000	0.0000	0.0000
Entergy New Orleans, Inc.	0.94	1.00	0.95	1.00	0.0084	0.0000	0.0076	0.0000
Niagara Mohawk Power Corporation	0.57	0.60	0.70	0.80	0.0158	0.0197	-0.0002	-0.0046
Northern Indiana Public Service Company	0.64	0.78	0.65	0.86	0.0217	0.0216	0.0239	0.0240
Northwestern Public Service	0.57	0.70	0.97	0.98	0.0195	0.0213	0.0078	0.0072
Ohio Edison Company	0.56	0.58	0.60	0.62	0.0446	0.0438	0.0416	0.0416
Oklahoma Gas and Electric Company	0.84	0.92	0.89	0.99	0.0104	0.0077	0.0098	0.0053
Orange and Rockland Utilities, Inc.	0.47	0.51	0.52	0.55	0.0599	0.0588	0.0483	0.0475
Otter Tail Power Company	0.76	0.83	0.84	0.89	0.0138	0.0111	0.0179	0.0137
Pacific Gas & Electric Co	0.53	0.63	0.85	0.98	0.0462	0.0597	0.0415	0.0175
PPL Electric Utilities Corporation	0.58	0.61	0.73	0.77	0.0226	0.0221	0.0176	0.0142
Potomac Electric Power Company	0.64	0.89	0.71	0.97	0.0227	0.0139	0.0196	0.0023
Public Service Company of New Mexico	0.47	0.65	0.51	0.66	0.0226	0.0154	0.0211	0.0164
Public Service Electric and Gas Company	0.52	0.73	0.75	0.91	0.0315	0.0375	0.0529	0.0241
Puget Sound Energy, Inc.	0.99	1.00	0.99	1.00	0.0027	0.0000	0.0016	0.0000
Rochester Gas and Electric Corporation	0.49	0.59	0.51	0.65	0.0503	0.0415	0.0420	0.0787
South Carolina Electric & Gas Company	0.67	0.70	0.70	0.74	-0.0050	-0.0034	0.0001	0.0003
Southern Indiana Gas and Electric Company	0.87	0.92	0.93	0.96	-0.0122	-0.0023	-0.0084	0.0000
Tampa Electric Company	0.68	0.80	0.70	0.83	-0.0002	-0.0019	0.0012	-0.0028
TXU Electric Company	0.78	0.92	0.99	1.00	-0.0021	0.0072	0.0000	0.0000
Texas-New Mexico Power Company	0.83	0.89	0.84	0.90	-0.0073	0.0000	-0.0072	0.0000
Tucson Electric Power Company	0.59	0.64	0.62	0.66	0.0032	0.0029	0.0006	0.0010
Union Electric Co	0.68	0.73	0.83	0.90	0.0194	0.0214	0.0133	0.0109
The United Illuminating Company	0.47	0.54	0.49	0.56	0.0551	0.0466	0.0485	0.0460
West Texas Utilities Company	0.80	0.94	0.86	0.96	0.0012	0.0221	0.0056	0.0191
Wisconsin Electric Power Company	0.82	0.84	0.91	0.97	-0.0042	-0.0051	0.0035	0.0086

Table 5. Average DEA Scores in Three Time Periods among All, Large, and Small Companies

		CCR	CCR4	BCC	BCC4
Overall	**1986-1990**	0.70	0.79	0.79	0.87
	1991-1995	0.72	0.80	0.79	0.88
	1996-2000	0.72	0.80	0.79	0.86
Large Companies	**1986-1990**	0.68	0.76	0.77	0.87
	1991-1995	0.68	0.77	0.77	0.87
	1996-2000	0.70	0.78	0.78	0.86
Small Companies	**1986-1990**	0.73	0.83	0.81	0.87
	1991-1995	0.77	0.84	0.82	0.89
	1996-2000	0.76	0.84	0.81	0.88

Table 6. Average DEA Growth Rates in Three Time Periods among All, Large, and Small Companies

		DCCR	DCCR4	DBCC	DBCC4
Overall	**1986-1990**	0.0135	0.0177	0.0177	0.0158
	1991-1995	0.0114	0.0041	0.0035	0.0016
	1996-2000	0.0225	0.0185	0.0154	0.0098
Large Companies	**1986-1990**	0.0181	0.0183	0.0239	0.0196
	1991-1995	0.0034	0.0048	0.0038	0.0006
	1996-2000	0.0231	0.0169	0.0136	0.0079
Small Companies	**1986-1990**	0.0065	0.0165	0.0082	0.0102
	1991-1995	0.0160	0.0021	0.0031	0.0036
	1996-2000	0.0093	0.0104	0.0077	0.0096

As a next step we focus on whether these DEA scores and growth rates are statistically significantly different over the three time periods, 1986-1990, 1991-1995, and 1996-2000. As mentioned earlier, we did not find very high DEA score changes (growth) between time periods. The null hypothesis that there are no significant differences in DEA scores in three time periods. This null hypothesis has been tested for all 74 utility companies, large, and small companies. The insignificant p-values of the DEA scores support the previous thoughts of the average DEA scores are not different in three time periods. In Table 7, the growth of all industry and large companies in the CCR and BCC models are significantly different in different time periods.

Table 7. P-Value Test Statistics* of DEA Efficiency Scores in three Time Periods among All, Large, and Small Companies

	Companies		
	All	**Large**	**Small**
CCR	0.049	0.069	0.066
CCR4	0.494	0.398	0.562
BCC	0.270	0.856	0.122
BCC4	0.326	0.477	0.534
DCCR	0.000	0.000	0.130
DCCR4	0.001	0.004	0.120
DBCC	0.003	0.010	0.167
DBCC4	0.002	0.019	0.089

** At the 0.05 significance level*

After analyzing the companies as whole industry, large, and small individually, we investigate whether there is a significant difference between large and small companies in each time period. Table 8 shows that the DEA efficiencies of large and small companies are significantly different than each other in each of the time periods, except for the BCC model with four output set. The average efficiency scores of small companies are higher than large companies. The lower efficiency scores of large companies could come from more bureaucracy in the large companies.

Table 8. ANOVA Table for Large/Small Company Differences in three Time Periods

CCR 1986-1990	0.274	10.121	0.002
CCR 1991-1995	0.689	25.056	0.000
CCR 1996-2000	0.279	10.541	0.001
CCR4 1986-1990	0.391	15.739	0.000
CCR4 1991-1995	0.554	23.044	0.000
CCR4 1996-2000	0.329	13.638	0.000
BCC 1986-1990	0.198	7.275	0.007
BCC 1991-1995	0.244	8.702	0.003
BCC 1996-2000	0.107	3.915	0.049
BCC4 1986-1990	0.001	0.064	0.800
BCC4 1991-1995	0.032	1.461	0.228
BCC4 1996-2000	0.022	0.991	0.320

On the other hand, the growths of these DEA models are not significantly different at the 0.05 level. We conclude that the efficiency score changes of large and small companies had the same growth rate in the same time period. However, large and small company efficiency scores are significantly different in the same time periods, except for the four-output-DEA model. Small utility companies are more efficient than large companies. Deregulation of the electricity market didn't make any difference on large and small company behavior of efficiency.

The output slack variables show how much additional output could be produced with the efficient level of input; and the input slack variables reveals how much proportional deduction is needed to achieve efficiency level. Major inefficiencies came from labor (Emp) and capital (NUP) inputs. Inefficiencies went down in the second period, 1991-1995, but material inefficiency went up. Labor and fuel inefficiencies went down during this time period (Table 8).

Table 9. Average Slack Variables by Time Periods

	OUTPUT SLACK VARIABLES				INPUT SLACK VARIABLES			
Years	RMWHS	CMWHS	IMWHS	OMWHS	Emp	NUP	QF	QO
1986-1990	3.55	1.09	1.39	0.47	220.09	1995.59	100.56	60.28
1991-1995	1.90	1.38	0.69	0.46	235.28	1261.25	59.46	117.30
1996-2000	0.18	0.78	2.62	1.42	166.31	1671.23	33.99	49.19

,where RMWHS, CMWHS, IMWHS, OMWHS are the electricity sold to the residential, commercial, industrial and other consumers as megawatthours, respectively; and Emp, NUP, QF and QO are the number of employees (Labor) worked at the electricity generation units, net utility plant (capital), quantity of fuel, and quantity of other expenditures including material, respectively.

4.2. Regulatory Effect on Efficiency Results

We used two different reports in order to measure regulatory effect on efficiency; one is the rankings of state regulatory commissions, published by Duff & Phelps, called friendliness; and the other is the report of what the states' position is in deregulation and restructuring, called the Retail Energy Deregulation (RED) Index. The difference between two reports is that the former measures the state commission's success in regulating the industry, and latter is the measurement of efforts in deregulating the electric power industry in the U.S.

Table 10 shows that the DEA scores (CCR, CCR4, and BCC, BCC4) are significantly different between more friendly and less friendly regulatory environments on average. The average productivity and efficiency levels of electric power companies in high friendliness states to the end users are higher than in a low friendliness states. It means tighter the state commission in a regulated environment is, higher the productivity and efficiency scores are. We do not detect any significant difference between more friendly and less friendly environments on average growth of productivity and efficiency.

Table 10. Test Statistics for Productivity Differences in More Friendly and Less Friendly States, 1986-1991

	squares	F	P-value
CCR	0.2590	9.395	0.002
CCR4	0.2680	11.352	0.001
BCC	0.2530	9.272	0.002
BCC4	0.1730	8.978	0.003
DCCR	0.0012	0.095	0.758
DCCR4	0.0016	0.203	0.653
DBCC	0.0005	0.056	0.813
DBCC4	0.0000	0.003	0.958

In the deregulation era from 1997 to 2000, in addition to the DEA scores, the changes in DEA (DCCR, DCCR4, DBCC, and DBCC4) of the utilities in higher the RED index scored states are significantly different than the utilities in lower RED index scored states (Table 11). The utility companies which operate in highly regulated states have higher productivity level and growth on average. This could be due towo reasons: early stages of the deregulation may cause the uncertainty for the near future and the differences of states in terms of accepting the level of restructuring.

Table 11. Test Statistics for Productivity Differences in High and Low RED Index Scored States, 1997-2000

	squares	F	P-value
CCR	0.2590	9.395	0.002
CCR4	0.2680	11.352	0.001
BCC	0.2530	9.272	0.002
BCC4	0.1730	8.978	0.003
DCCR	0.0012	0.095	0.758
DCCR4	0.0016	0.203	0.653
DBCC	0.0005	0.056	0.813
DBCC4	0.0000	0.003	0.958

Finally, we investigate whether there is a significant difference in between two time periods, 1986-1991 and 1997-2000 on average. Except for the BCC and BCC4 models of DEA, the other efficiency level scores are significantly different in two time periods on average (Table 12). The utility companies in a deregulated time period (1997-2000) are more productive than in a regulated time period of 1986-1991. Even though not all states in the U.S. accepted to change the market structure in electric power industry, they scored better in the period of 1997-2000 on average when we compare with the time period 1986-1991. This could be because of technological change, political influences, and financial reasons. Technological change in the electric power industry does not occur very fast, but solving the technical difficulties and learning-by-doing could be an effect on high productivity.

Table 12. Test Statistics for Productivity Differences in Two Time Periods (1986-1991 and 1997-2000)

	squares	F	P-value
CCR	0.2290	8.328	0.004
CCR4	0.1390	5.786	0.016
BCC	0.0404	1.478	0.224
BCC4	0.0184	0.919	0.338
DCCR	0.1340	11.051	0.001
DCCR4	0.1270	14.903	0.000
DBCC	0.1130	11.861	0.001
DBCC4	0.0791	10.791	0.001

The states in regulated industries are under considerable pressure in their decision making processes as whether to change the market structure to a competitive market. Since those states have the lowest electricity rates in the U.S. electricity market, the legislators are more favor on delaying to accept the competitiveness in the electric power market. In addition, possibility of changing the market structure in the near future could cause an increase in productivity of power companies to compete with other companies if any market structure changes.

5. Conclusion

In this study, efficiencies of the U.S. electric power companies were measured by using data envelopment analysis (DEA). We used the CCR model, introduced by Charnes et al. (1978) and the BCC model, introduced by Banker et al. (1984) in order to measure technical efficiencies of the utility companies.

DEA measures the efficiency of the decision making units (DMUs) by a linear programming technique to draw a piecewise frontier line. The DEA models that we used in this study the CCR and the BCC models have two possible orientation; input and output. We used input oriented DEA models with two different perspectives; one is the single output of aggregated all MWh sales to the customer, and the other one is the outputs of MWh sold to the residential, commercial, industrial, and other consumers.

We found that there is no significant difference in terms of efficiency scores, except for overall technical efficiency (CCR) for all companies in the industry; however, the growth rates are significant for the industry and large companies in each time period (1986-1990, 1991-1995, and 1996-2000). This means that technical efficiency growth may result in significant differences in average efficiency in the near future.

The efficiency scores of large and small companies are significant in a particular time period on average, but, we cannot conclude the significant differences of the growth rates among large and small companies.

The changes in output mix are not subject to regulatory control. Utility companies have their unique customer choices of residential, commercial, industrial, and other customer type. In this study, we used two types of output mix in the efficiency analysis: one is the aggregated output, and the other is MWh sold to the residential, commercial, industrial, and other consumers. In DEA, the efficiency model with four outputs has more efficient decision making units (DMUs) as we expected. The findings of efficiency differences between different time periods show that the efficiency growth in single output models (CCR and BCC) have a positive difference in the deregulated time period when we compare with other two time periods; however, the efficiency model with four outputs (CCR4 and BCC4) has the positive change in the deregulated time period, comparing with the second time period. This may be interpreted as utility companies focus on some customer types; therefore, when we disaggragate the sales of the all customer to the individual customers as residential, commercial, industrial, and other, more utility companies are found efficient.

Regulatory agency influence is very vital in the electric power industry, because, state and federal commissions have big impact on price, environmental, loading, and investment of the power companies. Although, the utility companies have higher efficiency scores between 1996 and 2000, we looked at which companies made the difference. As mentioned earlier, half of the states did not pass the deregulation laws. The states which accepted the restructuring efforts have higher electricity cost to the consumers. Our findings support that the higher efficiency in time period of 1996-2000 occured because of the utility companies which are still highly regulated in their states. There may be small increase on efficiency when the states deregulate the electric power industry, but, it is too early to make a strong conclusion about the benefits of the restructuring are achieved.

References

Banker, R.D., Charnes, A. and Cooper, W.W.,1984. Some models for estimating technical and scale inefficiencies in data envelopment analysis, Management Science.30(9), pp. 1078-1092.

Bagdadioglu, Necmiddin; Price, Catherine M. Waddams; Weyman-Jones Thomas G., (1996). " Efficiency and ownership in electricity distribution: A non-parametric model of the Turkish experience." Energy Economics, 18, pp. 1-23.

Bureau of Economic Analysis of U.S. Department of Labor, http://www.bea.doc.gov/bea/industry/iotables/prod/table_list.cfm?anon=52. Washington,D.C. 2003.

Bureau of Labor Statistics (BLS),. http://www.bls.gov, Washington,DC USA. 2003

Center for the Advancement of Energy Markets (CAEM) "The Retail Energy Deregulation Markets (RED) Index, Washington, D.C. ,March 2002.

Charnes, Abraham, Cooper, W.William, and Rhodes, Edwardo,1978. Measuring the efficiency of decisions making units, European Journal of Operational Research, 2(6), pp. 429-444

Charnes, Abraham; Cooper, William; Lewin, Arie Y. and Seiford, Lawrence M., Data Envelopment Analysis: Theory, Methodology and Applications, eds. Abraham Charnes, William Cooper, Arie Y. Lewin and Lawrence M. Seiford Kluwer Academic Publishers, Boston, 1994, pp.1-49

Chitkara, Puneet, "A data envelopment analysis approach to evaluation of operational inefficiencies in power generating units: A case study of Indian power plants." IEEE Transactions on Power Systems, 14 (2) , 1999,pp. 419-425.

Connolly, Haru, "Three essays on productivity and research and development in U.S. investor-owned electric utilities." Unpublished PhD Dissertation, University of California, Berkeley, 1997.

Diewert,W. Erwin and Nakamura, Alice O., "Benchmarking and the measurement of best practice efficiency: an electricity generation application", Canadian Journal of Economics 32 (2), 1999, pp. 570-588.

Duff & Phelps, Inc., " Synopsis of state regulatory commission practices." Regulatory developments public utility research division, 1986-1991.

Energy Information Administration (EIA), "The changing structure of the electric power industry: an update." DOE/EIA-0562(00), Washington D.C., 2000.

Federal Energy Regulatory Commission (FERC), Form 1 (Rev.12-98),. http://www.ferc.gov/docs-filing/eforms/form-1/viewer-instruct.asp, Wahington,DC 1986-2000.

Golany, B., Roll, Y., "An application procedure for DEA", Omega, 17 (3), 1989, pp. 237-250.

Golany, Boaz; Roll, Yaakov, and Rybak, David, "Measuring efficiency of power plants in Israel by data envelopment analysis." IEEE Transactions on Engineering Management 41 (3), August 1994, pp. 291-301.

Goto, Mika; Tsutsui, Miki. "Comparison of productive and cost efficiencies among Japanese and US electric utilities." Omega, Int. J. Mgmt Sci. 26 (2), 1998, pp.177-194.

Gurgen, E., 2003. "Efficiency and Stock Market Performances of Electric Power Generating Companies: A Comprehensive Analysis of Deregulation and Reregulation Era."Unpublished PhD Dissertation, Rensselaer Polytechnic Institute.

Nelson, Randy A. and Wohar, Mark E., "Regulation, scale economies, and productivity in steam-electric generation." International Economic Review. 24 (1), 1983, pp. 57-79.