Greenhouse Gas Emissions Effect on Cost Efficiencies of U.S. Electric Power Plants

Melissa Lynes, U.S. Energy Information Administration, melissa.lynes@eia.gov
Brady Brewer, University of Georgia, bebrewer@uga.edu
Allen Featherstone, Kansas State University, afeather@ksu.edu

Selected Paper prepared for presentation at the 2016 Agricultural & Applied Economics Association Annual Meeting, Boston, Massachusetts, July 31 – August 2

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Power plants are large producers of greenhouse gas emissions. The source of this pollution comes from raw material used to produce electricity. Since the 1950s, policies have been implemented and updated to regulate the emissions of certain pollutants from electricity production. In 1990, the Clean Air Act addressed pollutants associated with acid rain, ozone depletion, and toxic gases. Across the United States, this act reduced the intended pollutants. The main focus of the Obama Administration has shifted from pollutants that cause acid rain to those that are argued to affect climate change – greenhouse gases (GHGs). In 2015, a policy was introduced – the Clean Power Plan that focused on reducing greenhouse gas emissions. This included an emphasis on non-emitting sources - renewable and nuclear energy, efficiency improvements within homes and businesses, and reducing greenhouse gas emissions from coal, natural gas, and petroleum.

The purpose of the paper is to determine the potential impact of reducing greenhouse gas emissions on cost efficiencies of power plants. Using data envelopment analysis (DEA) we estimate the economic, allocative, and technical efficiencies of approximately 500 power plants in the United States with and without a constraint on emissions. Greenhouse gas emissions are included as "bad" outputs to understand the impact they have on the cost efficiencies of power plants. Reduction in emissions can occur for two reasons: firms using efficient technology from a cost perspective, or by constraining firms to have no more emissions in the cost minimizing case than they currently have.

Previous Studies

There have been two different approaches regarding undesirable outputs of electric generation plants within the DEA framework. The approach followed depends on the research question at hand. The first approach builds on the work of Charnes, Cooper, and Rhodes (1978) and Banker, Charnes, and Cooper (1984). This work is focuses on the production function of a firm. The second approach builds on the work of Färe et al. (1989) that focuses on determining the efficiency of a firm determined by the undesirable outputs. Färe et al. (1989) expanded upon the work of Farrell (1957) to develop a DEA model that allows for undesirable outputs to be incorporated into the model as weakly disposable.

Production Studies

One of the first studies to include undesirable outputs in a DEA analysis of electricity plants was Golany, Roll, and Rybak (1994). They determined the overall technical efficiency of 87 Israeli power plants operating in a closed market. Four outputs and three inputs were considered. The four outputs considered were generated power (MWh), operational availability, deviation from operational parameters, and sulfur dioxide (SO_2) emissions. SO_2 was measured in three levels as a set of binary codes with three levels: good, medium, and bad. Good implied that the plant is polluting at an acceptable emissions rate where there was one or less violation per quarter. Medium implied that there were between two and four violations per quarter while bad implied that there were five or more violations per quarter.

Yaisawarng and Klein (1994) considered how SO_2 control policies affect the efficiency of power plants in the U.S. They used overall technical, pure technical, and scale efficiencies to analyze the impact of these policies on 60 coal-fired plants from 1985 through 1989. They found that plants with scrubbers experience lower overall technical and pure technical efficiency levels than plants without scrubbers.

Raczka (2001) using a two-stage model estimates technical efficiency for 41 heat plants in Poland. The pure technical efficiency score is estimated in the first stage analysis using one output and three inputs. Instead of including pollution as an undesirable output, it is included as an input. The pollution variable is represented the amount the utility pays in penalties due to polluting. The average age and average capacity of the boilers are included in the second stage analysis of which neither are found to be statistically significant in measuring efficiency.

Arocena and Price (2002) determine the efficiency change, technological change, scale index, and the Malmquist productivity index of electricity producers in Spain from 1984 through 1997 as environmental regulation was being implemented. Five outputs and three inputs are used in the analysis including annual net power produced (GWh), availability, SO_2 (tons), NO_X (tons), and particulates (tons) [1]. They found that public firms were more efficient than private firms and that incentive regulation would increases efficiency of private firms.

Nag (2006) used DEA to estimate emissions for coal based thermal power generation for utility plants in India using a slack-based input-oriented pure technical efficiency for the plants. By calculating the slack, it allows the researchers to determine if there is excess input use after a proportional reduction in inputs. He found that plantwise energy conservations targets should be set to achieve the maximum reduction in emissions.

Sarica and Or (2007) determined the efficiencies of 65 thermal power plants in Turkey using overall technical and pure technical efficiencies. The model included four outputs and two inputs. The four outputs were availability, thermal efficiency, environmental cost, and carbon monoxide (CO) (tons). The two inputs included fuel cost and production (kWh). Three of the four output variables are undesirable. Thermal efficiency reflects the effects of CO emissions by

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[1] NO_X refers to nitrogen oxides.

converting heat dissipated into electric energy. When thermal efficiency is maximized, it implies that emissions are minimized. The environmental cost is the monetary value that is determined using dollars per ton of annual SO_2, NO_x, and particulate emissions of each plant.

Welch and Barnum (2009) evaluate what it would take for steam powered plants to move from the cost efficient point to the environmental efficient point. They find that it could be costly to move from the cost efficient point to the environmental efficient point, however for some firms, they could improve both their cost and environmental efficiencies by reducing the amount of input used.

Sozen, Alp, and Ozdemir (2010) created two efficiency indexes for state owned thermal plants in Turkey. One analysis focused on the slack-based overall technical efficiencies while the other focuses on environmental performance. The environmental performance model included emissions as outputs. The outputs taken into consideration are CH_4, N_2O, non-methane volatile organic compounds (NMVOC), CO, CO_2, mono-nitrogen oxide (NO_X), and SO_2 (all in tons).

In another study, Majumder and Marcus (2001) used a two-stage model to determine if the change in the 1970 Clean Air Act affected the overall technical and pure technical efficiencies of 150 of the largest investor-owned utilities in the U.S. in 1990. Instead of including pollution variables in the DEA analysis, they included numerous pollution variables in a second-stage tobit model.

Environmental Studies

In addition to looking at production based efficiencies several other DEA analysis have been used. Färe, Grosskopf, and Tyteca (1996) use a distance function and include the bad outputs SO_2, NO_X, and CO_2 in their DEA analysis. Tyteca (1997) compares three different approaches to analyzing the environmental efficiency of coal-fired power plants. There is one desirable and three undesirable outputs considered in the analysis – net generation (kWh), and SO_2, NO_X, and CO_2 (all in tons). The inputs considered include installed capacity (MW), coal (1,000 short tons), oil (100 bbls), gas (mmcf), and labor. They find that there are considerable differences between the ranking of firms based on the model that is used. However, they say that in order to decide which model is best, it likely depends on what the model is going to be used for. Since all of these models are designed to show which power plants are most environmentally efficient, simply showing a ranking might be sufficient enough to encourage the least environmentally efficient firms to reevaluate their production process and increase their environmental efficiency by decreasing their undesirable outputs.

Korhonen and Luptacik (2004) develop several different models to deal with undesirable outputs. The models used include: all outputs as a weighted sum where the bad outputs are negative; the bad outputs enter the analysis as inputs; the ratio of the weighted sum of desirable inputs minus the inputs of the undesirable outputs; and an output-oriented version of the aforementioned models. In order to test the models, 24 European power plants were studied. The desirable output included is electricity generation (MW) and the input is costs. The undesirable outputs include dust, NO_x, and SO_2. Comparing the results of the first three models, they find that similar results are obtained regardless of which model is used.

Xie, Fan, and Qu (2012) use a network DEA to determine the environmental efficiencies of 30 provincial administrative regions in China. They find that the percentage of thermal power versus clean energy power effects the environmental efficiency of a plant. In most years of the study, the electric generation plants that used at least 25% clean energy power were the most efficient plants. They also find that policies developed to incentivize clean energy development has achieved its objective. A single undesirable output is used in the analysis – CO_2.

Zhou et al. (2013) introduces a non-radial DEA approach that uses entropy weights to determine the environmental efficiency of the power industry in China. The three inputs are labor, investment, and energy. The three undesirable outputs are SO_2, NO_X, and CO_2. The energy and environmental efficiencies of 28 provinces' thermal power plants in China are determined by Bi et al. (2014) using a slack-based model. Four outputs and four inputs are considered. The four outputs include one good output – power generated (10^8 kWh), and three bad outputs – SO_2, NO_X, and soot (all in tons).

There are a series of studies by Sueyoshi and Goto that have two overarching goals. The first goal is to determine if the Clean Air Act has helped curtail SO_2 and NO_x pollution. The second goal is to determine an appropriate model to calculate the environmental efficiency of a firm in a given year or over a series of years. Analyzing coal-fired plants in the U.S., the three undesirable outputs analyzed are SO_2 (tons), NO_X (tons), and CO_2 (1000 tons). The one desirable output considered is net generation (MWh). Sueyoshi, Goto, and Ueno (2010) and Sueyoshi and Goto (2010) evaluate the plants' operational, environmental, and unified performance, where unified performance takes into account both operational and environmental aspects. The DEA model of choice is a range-adjusted measure model. They find that the Clean Air Act has helped to curtail SO_2 and NO_x pollution and conclude that the policy should be extended to also include CO_2.

Sueyoshi and Goto (2012) compare the results of radial and non-radial DEA analysis for the unified efficiencies of coal-fired power plants in the U.S. Both quantities and prices are used as input variables. The input variables include number of employees, total cost of the plant, total non-fuel operation and management cost, and fuel consumption (1000 tons). They find that there is not a large difference in using either the radial or non-radial models, however, the number of decision making units (DMUs) used can make a significant difference in the analysis. They recommend, whenever possible, it is better to use more DMUs. Two regional transmission organizations in the U.S. were compared by Sueyoshi and Goto (2013) to determine both their environmental and operational performances.

In 2013 two different time series analysis were conducted by Sueyoshi and Goto. One study creates a Malmquist index to take into account improvements in technology with respect to CO_2 emissions (Sueyoshi and Goto 2013). They find that there is a time lag with respect to technology innovation for electricity production and CO_2 emission reduction. The second proposes a DEA window analysis in order to capture the frontier shift for environmental assessment (Sueyoshi, Goto and Sugiyama 2013). Over the time frame of the study, the efficiency of coal-fired power plants has increased implying that the Clean Air Act has succeed in reducing pollution by coal-fired power plants. They suggest that a policy like the Clean Air Act should be implemented or extended to also control for CO_2 emissions.

The previous studies have taken one of two approaches when considering undesirable outputs in an efficiency analysis. The first is to include undesirable outputs as a component of a traditional production DEA analysis. The second approach is to develop an environmental efficiency that is less concerned with the production or costs of the firm and more concerned with the emissions of the firm. The current study more closely follows the first approach. This study contributes to the literature in a couple ways. First, this is one of the first DEA studies in the U.S. to only include greenhouse gas emissions as undesirable outputs instead of SO_2 that is heavily regulated and has been for decades whereas greenhouse gas emissions are not regulated in most states but may become regulated in the future. Second this study is the first to evaluate the effect that greenhouse gas emission have on cost efficiencies of U.S. electric power plants.

Methods

Electric generation plants, do not operate in a perfectly competitive market but they do minimize the costs of producing electricity. This implies that these firms should try to produce the highest level of output at the lowest cost. With the use of input such as coal, natural gas, and petroleum, electricity is produced as well as undesirable outputs such as carbon dioxide (CO_2), methane (NH_4), and nitrous oxide (NO_2). It is possible that electricity plants could reduce the undesirable outputs by simply improving cost efficiency.

Three input-oriented efficiency models are used in this study – allocative efficiency, economic efficiency, and technical efficiency. By considering all three types of cost efficiencies, and the corresponding shadow prices a firm is able to determine how best to adjust their production practices to become more efficient. A second set of the three efficiency models are estimated that takes into account the undesirable outputs in the model. In these models, the negative of the undesirable quantities are used as an output. This has the same effect as the firm trying to reduce the undesirable output.

All of the efficiency scores range from zero to one, where one implies the firm is efficient. For every type of efficiency, at least one DMU must have an efficiency score of one, however no DMU has to have an efficiency score of zero. In most DEA analysis multiple firms will have an efficiency of one. Those with an efficiency of one are on the cost frontier that all other firms try to reach. If a firm has a technical efficiency or an allocative score of less than one, this implies that the firm could become more efficient by using less inputs to reach the same level of output or a different mix of input, respectively. If the economic efficiency is one, this implies that the firm is operating on the variable cost frontier.

The economic efficiency is used to determine the cost frontier with variable returns to scale without consideration of the undesirable outputs. The frontier cost under variable returns to scale without consideration of the undesirable output is:

(1) $$\mathbf{\min \sum_{m=1}^{M} w_{mq} x_{mq}^{*}}$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq x_{mq}^{*} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} cap_k z_k \leq cap_q$$

$$\sum_{k=1}^{K} y_{rk} z_k \geq y_{rq} \quad \text{for } r = 1, \dots, R$$

$$-\sum_{k=1}^{K} b_{sk} z_k = r_q^{*} \quad \text{for } s = 1, \dots, S$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \dots, z_K) \geq 0,$$

where z is an intensity (or weight) of each electric generation plant k, x_{mk} are the inputs, w_{mq} are the input prices, y_k is the desirable output and b_k are the "bad" outputs of each electric generating plant k. Notice that the constraint simple adds up the amount of undesirable output and the frontier cost under variable returns to scale. There are M different inputs where x_{mq}^{*} is the optimal quantity of inputs.

The economic efficiency (EE) is ratio of the optimal minimum cost of producing the outputs and the observed costs under variable returns to scale.

$$EE_q = \frac{\sum_{m=1}^{M} w_{mq} x_{mq}^*}{\sum_{m=1}^{M} w_{mq} x_{mq}}$$

The economics cost efficiency model (equation 1) can be modified to include a constraint to require undesirable outputs to be less than or equal to the amount the firm is currently producing. The frontier variable returns to scale cost with an undesirable cost constraint is:

(2) $$\boldsymbol{\min \sum_{m=1}^{M} w_{mq} x_{mqc}^*}$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq x_{mqc}^* \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} cap_k z_k \leq cap_q$$

$$\sum_{k=1}^{K} y_{rk} z_k \geq y_{rq} \quad \text{for } r = 1, \dots, R$$

$$-\sum_{k=1}^{K} b_{sk} z_k \geq r_q \text{ for } s = 1, \dots, S$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \dots, z_K) \geq 0,$$

where the same definition exists as in the economic efficiency model with the exception that r_q is the amount of the undesirable of firm q and that x_{mqc}^* is the optimal input quantity with the undesirable output constraints.

Pure technical efficiency is a measure of how far off the production function a firm is, utilizing variable returns to scale. Pure technical efficiency is calculated by the following model:

(3) $\min \boldsymbol{\lambda_q}$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \boldsymbol{\lambda_q} x_{mq} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} cap_k z_k \leq cap_q$$

$$\sum_{k=1}^{K} y_{rk} z_k \geq y_{rq} \quad \text{for } r = 1, \dots, R$$

$$-\sum_{k=1}^{K} b_{sk} z_k = r_q^* \quad \text{for } s = 1, \dots, S$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \dots, z_K) \geq 0,$$

where λ_q is the measure of pure technical efficiency and the other variables follow from the model 1 above.

Pure technical efficiency with the undesirable output considered calculated by the following model:

(4) $$\min \boldsymbol{\lambda_{qc}}$$

Subject to:

$$\sum_{k=1}^{K} z_k x_{mk} \leq \boldsymbol{\lambda_{qc}} x_{mq} \quad \text{for } m = 1, \dots, M$$

$$\sum_{k=1}^{K} cap_k z_k \leq cap_q$$

$$\sum_{k=1}^{K} y_{rk} z_k \geq y_{rq} \quad \text{for } r = 1, \dots, R$$

$$-\sum_{k=1}^{K} b_{sk} z_k \geq r_q \text{ for } s = 1, \dots, S$$

$$\sum_{k=1}^{K} z_k = 1$$

$$(z_1, \dots, z_K) \geq 0,$$

Allocative efficiency for both models (AE) is determined by dividing the minimum cost from the constant returns to scale model by the actual cost multiplied by the pure technical efficiency. Allocative efficiency measures whether a firm is using the optimal input mix to produce the observed level of output. The formula for allocative efficiency is:

$$AE_q = \frac{\sum_{m=1}^{M} w_{mq} x_{mq}^*}{\sum_{m=1}^{M} w_{mq} \lambda_q x_{mq}}.$$

Data

Plant level data is used to determine the economic, allocative, and scale efficiencies for coal, natural gas, and petroleum power plants in 2012 in the U.S. Because only one year's data are used, we assume the law of one price, i.e., that all electricity producers faced the same relative input prices during 2012 (Featherstone, Langemeier and Ismet 1997). Thus, the cost data are used in the estimated models. The variable inputs used in the analysis are the fuel types and the fixed input is capacity. There are up to 12 different types of fuel included in the analysis (Table 1). The fuel sources are measured as total fuel consumption MMBTU (million British Thermal Units) annually. Capacity is net capacity in megawatts (MW) at the power plant. One desirable and three undesirable outputs are included in the analysis (Table 1). The one desirable output is net generation in megawatt hours (MWh). The three undesirable outputs are CO_2, NH_4, and N_2O measured in metric tons. There are 503 plants considered in the analysis.

The production and cost data comes from the U.S. Energy Information Administration (EIA) Form 923 (EIA 2015) and the greenhouse gas data comes from the U.S. Environmental Protection Agency (EPA) Greenhouse Gas Reporting Program (EPA 2015). Since the study focuses on power plants that emit greenhouse gases, only power plants that used only coal, natural gas, and/or petroleum are used in the analysis.

It is important to make sure there are enough degrees of freedom to estimate the DEA model. In general, there are enough degrees of freedom if the number of DMUs is greater than or equal to three times the number of inputs plus the number of outputs (Barros 2008). Given that the number of observations is 503, degrees of freedom is not an issue for even the disaggregate analysis (503 > 3(13+4 or 503>51).

Results

Without the consideration of undesirable outputs, the average economic efficiency is 14.8%, average pure technical efficiency is 24.1%, and the average allocative efficiency is 32.4% (Table 2). Of the 503 electric generation plants in the data, 26 were efficient in production (PTE) and 14 were on the minimum variable cost frontier. Constraining the undesirable output results in an average economic efficiency of 20.9%, average pure technical efficiency is 26.9%, and the average allocative efficiency is 52.1%. Of the 503 electric generation plants in the data, 34 were efficient in production (PTE) and 25 were on the minimum variable cost frontier constrained by undesirable outputs. Graphically for the unconstrained undesirable output, the frontier costs, predicted electricity generation, and the capacity are found in Figure 1.

The average amount of undesirable outputs are reported in Table 3 under the pure cost minimization model and the cost minimization with the undesirable outputs constrained. The actual level of undesirable output is also included for comparison purposes. If all firms would be on the cost frontier, the amount of carbon dioxide would be reduced by 69.6%, the amount of methane would be reduced by 59.2%, and the amount of nitrous oxide would be reduced by 66.8%. Choosing the cost minimizing technology to produce electricity would reduce undesirable outputs by more than 50%. Under the model where undesirable outputs are constrained, the additional amount of reduction is 47.5% for carbon dioxide, 76.6% for methane, and 77.7% for nitrous oxide. The correlation between electricity produced and the amount of reduction in the undesirable output are -0.252, -0.221, and -0.251 for carbon dioxide, methane, and nitrous oxide. The less electricity generated by a plant offers a larger opportunity for greenhouse gas emissions than at the larger plants. Certainly the constrained model suggests significant reduction, but in terms of metric tons if all firms achieved economic efficiency, there would be a significant decrease in the production of undesirable output.

While the average amount of undesirable output would decrease by moving to a cost minimization solution without consideration of undesirable output, 189 electric generation plants would increase carbon dioxide emissions, 271 electric generation plants would increase methane emissions, and 265 electric generation would increase nitrous oxides emissions. Further analyzing the cost under the undesirable output constraints, 58 electric generation plants were constrained by the amount of carbon dioxide ($C0_2$) produced, 59 were constrained by the amount of methane (NH_4) produced, and 224 were constrained by the amount of nitrous oxide ($N0_2$) produced (Table 4). For these constrained electric generation plants, the shadow cost of relaxing the output constraint was calculated. This represents the amount that costs could decrease if that constraint would be relaxed. Costs would decrease on average by $1,637 for carbon dioxide ($C0_2$), $647,964,439 for methane (NH_4), and $147,940,949 for nitrous oxide ($N0_2$). To put this in perspective, that is a cost reduction of 0.00001%, 3.00%, and 0.66% respectively for carbon dioxide($C0_2$), methane (NH_4) and nitrous oxide ($N0_2$) (Table 4). These results illustrate that the electric generation plants that are constrained in the amount of greenhouse gas emissions the plants produce could reduce cost without the undesirable output constraints.

Table 5 shows the breakdown of efficiency scores by those electric generation plants that were constrained by a greenhouse gas emission output and those that were not constrained. These results showed that the electric generation plants that were not constrained in the amount of greenhouse gas emissions they produced were more efficient with regards to the economic, allocative, and pure technical efficiency measures. Because the model accounted for greenhouse gas emissions as a negative input, the electric generation plants that polluted less are more efficient. Thus, the less the electric generation plants polluted, assuming the greenhouse gas emissions were constrained by policy, the more efficient they appear in the model. This analysis shows is the importance of limiting pollutants as an output in the production process as these policies would affecting the cost and production frontiers.

The efficiency results under the model with the undesirable outputs are further analyzed to examine how each greenhouse gas emission affects the allocative efficiency of each electric generation plan (Table 6). Both carbon dioxide ($C0_2$) and nitrous oxide ($N0_2$) were statistically significant. An increase in an electric generation plant's emissions of carbon dioxide ($C0_2$) is positively correlated with an increase in the allocative efficiency of the respective plant's input mix. An increase in nitrous oxide ($N0_2$) is also positively correlated with an increase in allocative efficiency. The effect of the greenhouse gas emissions on economic efficiency is the same as allocative efficiency with an increase in carbon dioxide ($C0_2$) and nitrous oxide ($N0_2$) emissions increases the economic efficiency. For pure technical efficiency, an increase in nitrous oxide ($N0_2$) emissions is positively correlated with pure technical efficiency and a decrease in methane emissions is negatively correlated with pure technical efficiency (Table 7).

Conclusions

Nonparametric Data Envelopment Analysis (DEA) models were used to estimate cost and production frontiers of 503 electric generation plans in 2012. The undesirable outputs of carbon dioxide($C0_2$), methane (NH_4) and nitrous oxide ($N0_2$) were considered. Results of models of short-run cost minimization without consideration of undesirable outputs were compared to models were the undesirable outputs were constrained.

Results showed if all firms were on the efficiency cost frontier, the amount of carbon dioxide could be reduced by 69.6%, the amount of methane could be reduced by 59.2%, and the amount of nitrous oxide could be reduced by 66.8%. Inefficiency in the production of electricity also result in the additional release of undesirable outputs. However, the release of all undesirable outputs would results in a decrease by moving to a cost minimization solution without consideration of undesirable output as 189 electric generation plants would increase carbon dioxide emissions, 271 electric generation plants would increase methane emissions, and 265 electric generation would increase nitrous oxides emissions. The correlation between the reduction in undesirable output reduction and the amount of electricity generated is negative indicating that smaller plants have greater opportunity for reduction in undesirable outputs by becoming cost efficient.

When adding a constraint for the undesirable outputs, further reduction of carbon dioxide, methane, and nitrous oxide would occur with an additional decline of 47.5%, 76.6%, and 77.7%, respectively. When the model accounts for greenhouse gas emissions as a bad output, the electric generation plants that were constrained were more efficient by most of the efficiency measures. This shows that the inclusion of a pollutant, in this case the greenhouse gas emissions of an electric generation plant, are accounted for in the production process, the efficiency scores and the frontier curves of the plant are affected and must be examined.

References

Arocena, Pablo, and Catherine Waddams Price. 2002. "Generating Efficiency: Economic and Environmental Regulation of Public and Private Electricity Generators in Spain." *International Journal of Industrial Organization* 41-69.

Banker, R. D., A. Charnes, and W. W. Cooper. 1984. "Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis." *Management Sciences* 1078-1092.

Barros, Carlos Petana. 2008. "Efficiency Analysis of Hydroelectric Generating Plants: A case study in Portugal." *Energy Economics* 59-75.

Bi, Gong-Bing, Wen Song, P. Zhou, and Liang Liang. 2014. "Does Environmental Regulation Affect Energy Efficiency in China's Thermal Power Generation? Empirical evidence from a slacks-based DEA model." *Energy Policy* 537-546.

Charnes, A., W.W. Cooper, and E. Rhodes. 1978. "Measuring the Efficiency of Decision Making Units." *European Journal of Operational Research* 429-444.

EIA. 2015. "Electricity." *U.S. Energy Information Administration.* March 23. Accessed April 24, 2015. http://www.eia.gov/electricity/data.cfm#revenue.

EPA. 2015. *Greenhouse Gas Reporting Program.* March 1. http://www.epa.gov/ghgreporting/.

Fallahi, Alireza, Reza Ebrahimi, and S. F. Ghaderi. 2011. "Measuring Efficincy and Productivity Change in Power Electric Generation management companies by Using Data Envelopment Analysis: A case study." *Energy* 6398-6405.

Fare, Rolf, Shawna Grosskopf, and Daniel Tyteca. 1996. "An Activity Analysis Model of the Environmental Performance of Firms - Application to Fossil-Fuel-Fired Electric Utilities." *Ecological Economics* 161-175.

Fare, Rolf, Shawna Grosskopf, C. A. K. Lovell, and Carl Pasurka. 1989. "Multilateral Productivity Comparisons When Some Outputs are Undesirable: A nonparametric approach." *The Review of Economics and Statistics* 90-98.

Farrell, M. J. 1957. "The Measurement of Productive Efficiency." *Journal of the Royal Statistical Society (Series A)* 253-290.

Featherstone, A.M., M.R. Langemeier, and M. Ismet. 1997. "A Nonparametric Analysis of Efficiency for a Sample of Kansas Beef Cow Farms." *Journal of Agricultural and Applied Economics* 175-184.

Golany, Boaz, Yaakov Roll, and David Rybak. 1994. "Measuring Efficiency of Power Plants in Israel by Date Envelopment Analysis." *IEEE Transactions on Engineering Management* 291-301.

Greene, William H. 2007. *Econometric Analysis Sixth Edition.* Upper Saddle River: Pearson .

Korhonen, Pekka J., and Mikulas Luptacik. 2004. "Eco-efficiency Analysis of Power Plants: An extension of Data Envelopment Analysis." *European Journal of Operational Research* 437-446.

Majumdar, Sumit K., and Alfred A. Marcus. 2001. "Rules Versus Discretion: The productivity consequences of flexible regulation." *The Academy of Management Journal* 170-179.

Nag, Barnali. 2006. "Estimation of Carbon Baselines for Power Generation in India: the supply side approach." *Energy Policy* 1399-1410.

Raczka, Jan. 2001. "Explaining the Performance of Heat Plants in Poland." *Energy Economics* 355-370.

Sarica, Kemal, and Ilhan Or. 2007. "Efficiency Assessment of Turkish Power Plants Using Data Envelopment Analysis." *Energy* 1484-1499.

Sozen, Adnan, Ihsan Alp, and Adnan Ozdemir. 2010. "Assessment of Operational and Environmental Performance of the Thermal Power." *Energy Policy* 6194-6203.

Sueyoshi, Toshiyuki, and Mika Goto. 2013. "A Comparative Study Among Fossil Fuel Power Plants in PJM and California ISO by DEA Environmental Assessment." *Energy Economics* 130-145.

Sueyoshi, Toshiyuki, and Mika Goto. 2013. "DEA Environmental Assessment in a Time Horizon: Malmquist Index on Fuel Mix, Electricity, and CO2 of Industrial Nations." *Energy Economics* 370-382.

Sueyoshi, Toshiyuki, and Mika Goto. 2012. "DEA Environmental Assessment of Coal Fired Power Plants: Methodological comparison between radial and non-radial models." *Energy Economics* 1854-1863.

Sueyoshi, Toshiyuki, and Mika Goto. 2010. "Should the US Clean Air Act Include CO2 Emission Control? Examination by data envelopment analysis." *Energy Policy* 5902-5911.

Sueyoshi, Toshiyuki, Mika Goto, and Manabu Sugiyama. 2013. "DEA Window Analysis for Environmental Assessment in a Dynamic Time Shift: Performance assessment of U.S. coal-fired power plants." *Energy Economics* 845-857.

Sueyoshi, Toshiyuki, Mika Goto, and Takahiro Ueno. 2010. "Performance Analysis of US Coal-Fired Power Plants by Measuring Three DEA Efficiencies." *Energy Policy* 1675-1688.

Tyteca, Daniel. 1997. "Linear Programming Models for the Measurement of Environmental Performance of Firms - Concepts and empirical results." *Journal of Productivity Analysis* 183-197.

Welch, Eric, and Darold Barnum. 2009. "Joint Environmental and Cost Efficiency Analysis of Electricity Generation." *Ecological Economics* 2336-2343.

Xie, Bai-Chen, Ying Fan, and Qian-Qian Qu. 2012. "Does Generation Form Influence Environmental Efficiency Performance? An analysis of China's power system." *Applied Energy* 261-271.

Yaisawarng, Suthathip, and J. Douglass Klein. 1994. "The Effects of Sulfer Dioxide Controls on Productivity Change in the U.S. Electric Power Industry." *The Review of Economics and Statistics* 447-460.

Zhou, Yan, Xinpeng Xing, Kuangnan Fang, Dapeng Liang, and Chunlin Xu. 2013. "Environmental Efficiency Analysis of Power Industry in China Based on an Entropy SBM model." *Energy Policy* 68-75.

Figure 1. Variable Cost Frontier for Electric Generation Plants in 2012

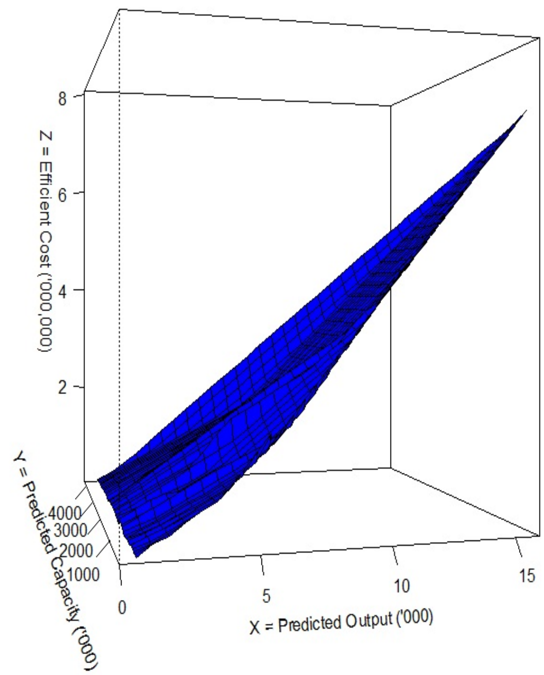

Table 1. Input and Output Summary Statistics of Electric Generation Plants in 2012

	Mean	Standard Deviation
	Total Input Cost	
Bituminous Coal	114,957,271	324,254,291
Sub-Bituminous Coal	115,966,961	315,823,307
Lignite Coal	12,179,903	105,099,065
Distillate Fuel Oil	16,094,204	36,947,162
Jet Fuel	747	16,739
Kerosene	149,182	3,342,478
Petroleum Coke	1,062,272	10,261,008
Residual Fuel Oil	1,313,195	22,261,324
Waste/Other Oil	81,757	1,066,450
Natural Gas	22,229,367,111	346,337,078,376
Other Gas	26,722,242	587,175,643
Gaseous Propane	31,985	324,254,291
Installed Capacity	819	719
	Output Quantity	
Net Generation	804,447	1,987,649
Carbon Dioxide (CO_2)	2,364,548	3,430,488
Methane (CH_4)	185	374
Nitrous Oxide (N_2O)	35	59

Table 2. Mean Efficiency Scores of Electric Generation Plants, 2012

Efficiency Measure	Unconstrained Model	"Bad" Output Constrained Model
Economic Efficiency	14.83%	20.93%
Pure Technical Efficiency	24.10%	26.89%
Allocative Efficiency	32.39%	52.06%

Table 3. Average Undesirable Outputs for Electric Generation Plants in Metric Tons, 2012

Undesirable Output	Actual	Unconstrained Model	"Bad" Output Constrained Model
Carbon Dioxide (CO_2)	2,364,548	719,823	377,781
Methane (CH_4)	185	75	18
Nitrous Oxide (N_2O)	35	11	3

Table 4. Marginal Costs of Undesirable Output Constraints, 2012

Undesirable Output	Number Constrained	Average Shadow Value	Standard Deviation	Percent of Total Cost
Carbon Dioxide (CO_2)	58	1,637	685	0.00001%
Methane (CH_4)	59	647,964,439	1,149,278,316	3.00%
Nitrous Oxide (N_2O)	224	147,940,949	211,061,837	0.66%

Numbers represent the amount total cost would decrease if pollution constraint would be relaxed at the frontier.

Table 5. Mean Efficiency Scores of Electric Generation Plants by Emission Constraints, 2012

	Economic Efficiency	Pure Technical Efficiency	Allocative Efficiency
	If Constrained by Greenhouse Gas Emissions		
Carbon Dioxide (CO_2)	0.481	0.517	0.858
Methane (CH_4)	0.470	0.490	0.808
Nitrous Oxide (N_2O)	0.281	0.317	0.796
	Not Constrained by Greenhouse Gas Emissions		
Carbon Dioxide (CO_2)	0.174	0.237	0.477
Methane (CH_4)	0.175	0.240	0.482
Nitrous Oxide (N_2O)	0.152	0.231	0.299

Table 6. Tobit Model, Allocative Efficiency, 2012

Efficiency Measure	Parameter	Standard Error	Test Statistic
Intercept	-1.083000***	0.038780	-27.935000
Carbon Dioxide (CO_2)	0.000000***	0.000000	-6.987000
Methane (CH_4)	-0.000145	0.000101	-1.439000
Nitrous Oxide (N_2O)	0.015100***	0.001610	9.377000

***Significant at 1%, **Significant at 5%, *Significant at 10%

Table 7. Tobit Model, Economic Efficiency, 2012

Efficiency Measure	Parameter	Standard Error	Test Statistic
Intercept	-1.323000***	0.038410	-34.456000
Carbon Dioxide (CO_2)	0.000000***	0.000000	-9.551000
Methane (CH_4)	-0.000091	0.000078	-1.167000
Nitrous Oxide (N_2O)	0.011980***	0.001125	10.651000

***Significant at 1%, **Significant at 5%, *Significant at 10%

Table 8. Tobit Model, Pure Technical Efficiency, 2012

Efficiency Measure	Parameter	Standard Error	Test Statistic
Intercept	-1.266000***	0.036960	-34.268000
Carbon Dioxide (CO_2)	0.000000	0.000000	-8.169000
Methane (CH_4)	-0.000106***	0.000079	-1.329000
Nitrous Oxide (N_2O)	0.011980***	0.001125	10.651000

***Significant at 1%, **Significant at 5%, *Significant at 10%