Energy Policy 37 (2009) 4574–4582

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

Does regulation stimulate productivity? The effect of air quality policies on the efficiency of US power plants

Rachel Fleishman [a], Rob Alexander [a,*], Stuart Bretschneider [b], David Popp [c,d]

[a] Department of Public Administration, the Maxwell School, Syracuse University, 215 Eggers Hall, Syracuse, NY 13244, United States
[b] Department of Public Administration, Center for Environmental Policy and Administration, the Maxwell School, 419 Crouse-Hinds Hall, Syracuse, NY 13244, United States
[c] Department of Public Administration, the Maxwell School, Syracuse University, 426 Eggers Hall, Syracuse, NY 13244, United States
[d] National Bureau of Economic Research, Cambridge, MA 02138, United States

ARTICLE INFO

Article history:
Received 29 May 2008
Accepted 2 June 2009
Available online 27 June 2009

Keywords:
Data envelopment analysis
Air pollution
Regulation

ABSTRACT

This research examines the effect of air quality regulations on the productivity of US power plants based on both economic and environmental outputs. Using data envelopment analysis (DEA) to estimate an efficiency measure incorporating both economic and environmental outcomes, we look at changes in efficiency in US power plants over an eleven-year time period (1994–2004) during which several different regulations were implemented for the control of nitrogen oxides (NO_x) and sulfur dioxide (SO_2). The paper then models how estimated efficiency behaves over time as a function of regulatory changes. Findings suggest mixed effects of regulations on power plant efficiency when pollution abatement and electricity generation are both included as outputs.

1. Introduction

Since the passage of the 1970 Clean Air Act, there has been steady public support for the regulation of US manufacturing and electrical generation plants. Over time, new health concerns and evolving theories about regulatory design have focused the character of these regulations, yet they have retained their broad scope and authority. Current regulations are largely based on the 1990 Clean Air Act, which introduced market-based reforms – such as permit trading – to allow firms greater flexibility in meeting air quality standards.

Dramatic improvements in US air quality since 1970 have led many to assume that regulations have worked. Scholarly studies of manufacturing plants show, in fact, that these regulations have reduced plant emissions levels (e.g., Shadbegian and Gray, 2003; Cole et al., 2005). However, studies also show that air quality regulations have a dampening effect on plant productivity (e.g., Gollop and Roberts, 1983), contributing to detrimental effects on the economy such as loss of jobs and capital stock (Greenstone, 2002) and regressive impacts on household earnings (Hollenbeck, 1979). As regulatory compliance becomes increasingly costly, and market-based reforms emerge to address this cost, it is a critical time to evaluate the impacts of both command-and-control and market-based regulations on environmental and economic goals. In this paper, we use data envelopment analysis (DEA) followed by a TOBIT regression analysis to examine the effect of specific environmental regulations on plant-level economic and emissions outcomes simultaneously. Specifically, *how have regulatory programs for sulfur dioxide* (SO_2) *and nitrogen oxide* (NO_x) *affected the pollution abatement and productivity of US power plants?*

This question could be asked at various levels of analysis. For instance, some scholars use emissions measures aggregated to the state level (Ringquist, 1993), while others use ambient pollution concentration measures at the county level (Greenstone, 2004). We follow the lead of production economists and focus on firm-level emissions and productivity (e.g., Färe et al., 2001, 2006; Olatubi and Dismukes, 2000; Shadbegian and Gray, 2005, 2006). This provides a fine-grained analysis, allowing us to examine how firms respond to regulation. We focus our analysis on US power plants, since these have been the target of major regulatory efforts in the past fifteen years.

Understanding the regulatory effects on our efficiency measure requires the integration of two different bodies of research that do not normally intersect—productivity research and evaluation of environmental regulations. Productivity research develops and tests different methods for measuring firms' technical efficiency, normally focusing on production as the output. Studies evaluating environmental regulations, on the other hand, primarily examine the relationship between environmental policy design and environmental outcomes. We link these literatures by first applying DEA to create an integrated measure of efficiency and then using TOBIT analysis to examine the impact of multiple regulation types on this measure. Understanding these impacts ultimately improves decision-making capabilities of policy

* Corresponding author. Tel.: +1 315 4433693; fax: +1 315 4433818.
E-mail address: rwalexan@syr.edu (R. Alexander).

0301-4215/$ - see front matter © 2009 Elsevier Ltd. All rights reserved.
doi:10.1016/j.enpol.2009.06.012

makers by allowing simultaneous evaluation of both environmental and economic outcomes (Tyteca, 1996).

We contribute in several ways to emerging research. First, we include two negative outputs – emissions of SO_2 and NO_x – in our efficiency measure. Because these pollutants have been a primary focus of recent regulatory changes in the 1990 Clean Air Act, it is critical to deepen our understanding of the environmental and economic impacts of both SO_2 and NO_x regulations. Second, previous research utilizing sophisticated efficiency measures like DEA has not examined how distinct regulatory forms affect these measures. By keeping regulation outside of the efficiency measure, we are able to model the separate efficiency impacts of various forms of SO_2 and NO_x regulation. Finally, our sample size, which includes 159 coal-fired and 171 gas-fired plants and covers an eleven-year period from 1994 to 2004, exceeds that of recent studies at the firm level.[1]

2. Literature review

2.1. From economic productivity to environmental performance

Production economics research has traditionally focused on production inputs and outputs when measuring firm efficiency. From this perspective, a highly technically efficient firm maximizes unit outputs per unit inputs. For power plants, this means maximizing the amount of electricity generated per unit of fuel, labor, and capital input. Environmental benefits – and the investment that goes into them – have subsequently been treated as diversions from primary production goals (Gollop and Roberts, 1983; Shadbegian and Gray, 2005). However, scholars are beginning to incorporate such social values into their measures of productivity (e.g., Tyteca, 1996, 1997; Boyd et al., 2002; Färe et al., 2001, 2006). As Smith and Sims (1985) point out, we may find that 'productivity' actually rises with greater regulation after accounting for environmental performance.

Environmental performance measures are 'analytical tools that allow one to compare various plants in a firm, or various firms in an industry, with each other … with respect to certain environmental characteristics' (Tyteca, 1996, p 281). Demand for these measures is rising due to pressure on firms from consumers, interest groups, and regulatory agencies to disclose emissions information and demonstrate environmental improvements. By developing standardized, aggregate environmental performance measures we can compare and rank firms across industry subsectors (Tyteca, 1996).

Researchers have explored multiple approaches to incorporate environmental performance in productivity analyses. For instance, Aiken and Pasurka Jr. (2003) calculate shadow prices for emissions and use these to adjust a traditional measure of total factor productivity, accounting for the reallocation of resources from production to pollution abatement activities. Several scholars use the Malmquist–Luenberger (ML) productivity index developed by Chung et al. (1997), which 'credits the producer for simultaneously reducing the level of bad outputs and increasing the level of good outputs' (Färe et al., 2001, p. 382). Similarly, Färe et al. (2006) employed an 'Environmental Performance Index' (EPI) that measures good output produced per unit of bad output.

Tyteca (1996) reviews and evaluates several types of environmental performance measures and finds the most versatile to be non-parametric measures that account for pollution in the form of 'undesirable outputs'. The measure we develop for our analysis – one example of this type – is derived from a linear programming model called data envelopment analysis. Through DEA, we can rank US power plants by their efficiency in using inputs to simultaneously produce electricity and limit emissions of harmful pollutants.

2.2. Regulatory impacts on firms' production and environmental efficiency

Most research on the regulatory impact of firm efficiency treats firm financial performance and environmental performance separately. While many studies of this nature find that spending on pollution abatement 'crowds out' productive investments (Boyd and McClelland, 1999; Gollop and Roberts, 1983; Shadbegian and Gray, 2006), a few studies determine that inputs and pollution can be reduced without compromising productivity (Boyd and McClelland, 1999; Murty et al., 2007). Other scholars find that certain types of regulatory activity, such as flexible market-based requirements and non-inspection regulatory activities, have a positive effect on traditional productivity (Shadbegian and Gray, 2006; Majumdar and Marcus, 2001; Berman and Bui, 2001) or that negative effects on productivity are insignificant (Färe et al., 1989, 2007).

A few studies have examined financial and environmental performance together. Färe et al. (2006, p. 259) find that power plants participating in Phase I of the Acid Rain Program (the initial phase of sulfur emissions trading) showed 'dramatic improvement' in their Environmental Performance Index during their year of participation. The EPI, as mentioned above, is an adjusted productivity measure of one good output (electrical generation) and one bad output (SO_2 emissions). In a different study, Färe et al. (2007) find no significant difference in the productivity growth of regulated versus unregulated technologies when productivity measures included jointly produced good and bad outputs. We advance this emerging body of research by expanding the efficiency measure to include NO_x as a negative output and by modeling the separate efficiency effects of multiple SO_2 and NO_x regulations.

3. Methods

Our methodology consists of two parts. First, we develop our DEA efficiency measure, which ranks the technical efficiency of US power plants on a scale from 0 (technically inefficient) to 1 (fully efficient). Given the censored nature of DEA estimates, we then employ a TOBIT model to examine the effects of SO_2 and NO_x regulation on the DEA score. This two-step methodology is most appropriate because it utilizes a versatile, robust efficiency measure (the DEA) that allows for the incorporation of multiple outputs and it allows us to separately model the effects of different regulatory types.

3.1. Overview of DEA[2]

Data envelopment analysis is a linear programming model that assigns a score to decision-making units (or firms) on a scale of 0–1 based on how efficiently they convert inputs into outputs. DEA estimates a 'best-practice' frontier using the given set of firms, and then places each firm on or below the frontier based on their relative technical efficiency. Because there are several unique combinations of inputs and outputs, more than one firm may

[1] A recent comprehensive study of coal-fired power plants in the US had a sample size of 92 (Färe et al., 2007).

[2] For a more detailed mathematical description, see Olatubi and Dismukes (2000).

receive the same score, including the ‘fully efficient’ score of ‘1’. Also, the least efficient firm may not receive a score of ‘0’. DEA measures can be tailored to include any input/output mixture, including negative outputs like pollution. Thus, the DEA measure can simultaneously credit firms for increasing good output and for decreasing bad output (Boyd and McClelland, 1999).

A key advantage of DEA is that no weights are needed for the inputs and outputs. This avoids the problem of assigning values for production versus pollution abatement, or abatement of one pollutant versus another (Färe et al., 2004). Additional advantages include the standardization provided by the 0–1 scale, the flexibility of the model in accommodating different sets of inputs and outputs, and the robustness of the linear programming method (Färe et al., 1996). Finally, DEA indicators can be used to ‘uncover determinants of inefficiency’ (Olatubi and Dismukes, 2000, p. 57) by comparing the input/output mixes of efficient and inefficient firms, making DEA a useful tool for identifying slack and targeting resources to be used most efficiently (Lam and Shiu, 2004). Disadvantages of DEA include sensitivity to outliers (Tyteca, 1997; Olatubi and Dismukes, 2000) and sensitivity to unique combinations of inputs and outputs (Färe et al., 1996). DEA estimates *relative* efficiencies and therefore can be subject to changes when new cases are included in the analysis.

3.2. Developing our DEA measures of efficiency

Our primary DEA measure of efficiency includes five inputs and three outputs. The inputs are labor (measured by number of employees), capital (a summation of land, structure, and equipment costs), and energy provided by coal, petroleum, and gas (in British Thermal Units (BTUs)). The outputs include electricity generated, SO_2 emissions, and NO_x emissions. Both emissions measures enter the DEA as negative outputs. We also create a secondary DEA measure of efficiency omitting the two pollutants to better understand the implications of including multiple outputs in DEA estimates of efficiency.

A basic underlying assumption embedded in DEA scores is that all firms in the analysis share a common production process. Because the production process for electricity depends on the fuel source, we segmented our estimates into subgroups of plants based on the predominant fuel source. A plant was placed into a fuel category if at least 95% of the energy it produces came from that fuel. Petroleum plants were dropped because there were too few for analysis.

Our unit of analysis is the plant-year (e.g. plant number 3 in the year 1995). This means that each plant receives a DEA score for each year in which the DEA input and output variables are available. Six plants switch from 95% of one fuel to 95% of the other fuel. In this case, the same plant shows up in both the coal and gas DEA rankings, depending on its fuel consumption pattern in that year.

3.3. TOBIT model

We use TOBIT analysis, because the DEA produces a variable left-censored at zero and right-censored at one. For the TOBIT model, we inverted the DEA score to create a left-censored continuous-dependent variable. Independent variables included regulation measures (Table 1) and a vector of control variables (Table 2).

The general model is

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_2 X_3 \varepsilon$$

where Y is the inverse DEA score (for a given plant-year), X_1 is a vector of dummy variables representing relevant SO_2 and NO_x regulations, X_2 is a vector of variables representing the level of these SO_2 and NO_x regulations, and X_3 is a vector of control variables.

Separate analyses were performed for coal and gas plants, and using DEA scores with and without pollution outputs. Thus, four separate TOBIT analyses were conducted.

Table 1
Regulation variables for SO_2 and NO_x.

SO_2 regulation types	
SO_2 limit	lbs of SO_2 allowed per million BTUs of fuel
Lbs SO_2/h	lbs of SO_2 allowed per hour
Pct sulfur	Percent sulfur content of fuel allowed, by weight
PPM SO_2	Parts per million of SO_2 allowed in stack gas
NO_x regulation types	
NO_x limit	lbs of NO_x allowed per million BTUs of fuel
Lbs NO_x/h	lbs of NO_x allowed per hour
PPM NO_x	Parts per million of NO_x allowed in stack gas
NO_x ambient	Ambient air quality concentration of NO_x allowed (ppm)
Other regulation dummy variables	
No SO_2 regulation	No SO_2 regulations apply
No NO_x regulation	No NO_x regulations apply
SO_2 trade (coal only)	Dummy variable indicating start of widespread SO_2 trading
Phase1 (coal only)	Dummy variable indicating plant participated in phase 1

Table 2
Control variables.

Control variable	Description
Year	Year
State	State in which a plant is located
Age constructed	Year minus year of original construction
Total capacity	Maximum generation name plate ratings (megawatts)
Heat content coal	BTU/lb (measure of fuel quality)
Heat content gas	BTU/ft^3 (measure of fuel quality)
Sulfur content coal	Sulfur content of coal
Switch fuel	Plant switches from 95% of one fuel to 95% of other
FERC drop	Plant dropped out of FERC dataset (i.e., was privatized)

3.4. Regulation and control variables

In a power plant, each boiler is subject to its own set of federal, state, and local regulations. We selected the most stringent SO_2 and NO_x regulations that apply to each boiler and aggregated these measures to create plant-level regulation variables. Table 1 describes eight different regulation types (four each for SO_2 and NO_x) included in the X_1 and X_2 vectors. For each regulation type, we created two forms of aggregate measures: a ‘dummy’ to capture the qualitative presence of the regulation and a ‘level’ variable representing the regulation’s stringency. For dummy variables, plant-years received a ‘1’ if at least one boiler was under that regulation type. Level variables were created by averaging the stringency level over all boilers that carried that regulation type, weighted by the proportion of total energy consumed by each boiler in that year. This weighted average was then multiplied by the percent of total boilers under that regulation in that plant. It is important to note that all the regulation variables represent an allowable limit, so higher levels mean less stringency. We inverted the weighted average so the final ‘regulation level’ variables increase in magnitude with increasing regulatory stringency.

At the bottom of Table 1 are four regulation dummy variables that do not have a corresponding level variable. ‘No SO_2 Regulation’ and ‘No NO_x Regulation’ represent plant-years without any regulation for SO_2 and NO_x, respectively. There are also two dummy variables for SO_2 permit trading. ‘Phase1’ indicates that the plant had at least one boiler participating in Phase 1 of the Acid Rain Program, which targeted only the dirtiest coal-fired boilers. The dummy variable 'SO_2 Trade' indicates the start of Phase 2 of the Acid Rain Program in 2000, which opened up SO_2 emissions trading to all coal-fired boilers. Because 'Phase1' and 'SO_2 Trade' affect only coal-fired plants, they are excluded from TOBIT analyses on the gas dataset.

Plant-years subject to more than one regulation type for SO_2 or NO_x comprised less than 10% of the total observations, and were removed from the dataset. Thus, exclusive of 'Phase1' and 'SO_2 Trade', each plant-year is represented by only one SO_2 and one NO_x regulation type.

Control variables are listed in Table 2 below and derive from existing research on power plant productivity and environmental policy analysis (Färe et al., 2006). They are the same for gas and coal TOBIT models, except for the fuel quality measures 'Sulfur Content Coal' and 'Heat Content Coal', which are specific to coal plants, and 'Heat Content Gas', which is specific to gas plants.

The control variable 'year' captures technological changes and political events that affect the power industry. 'State' implements state fixed-effects to control for differences in regulatory agencies, regulatory structures, and geographical constraints (such as proximity to fuels). 'Age constructed' controls for technological constraints and costs associated with older plants, while 'total capacity' captures the expected advantage of larger plants, due to economies of scale. The 'heat content' and 'sulfur content' of fuel are expected to have a separate effect on plant efficiency (apart from regulation); thus they are important controls. 'Switch fuel' indicates the capacity of plants to switch from 95% of one fuel to 95% of another within the eleven year period. We expect plants with this added flexibility to be more efficient. 'FERC drop' indicates that a plant was privatized during this period, and thus drops out of the FERC database. This allows us to test whether plants sold to private investors differ from plants that remain in the hands of regulated public utilities.

3.5. Data sources and final data sets

Our data derive from a variety of sources. Energy Information Administration (EIA) form EIA-767, a survey distributed annually to US power plants during our study period, provided information at the individual boiler level for all regulation variables excluding 'Phase1' and 'SO_2 Trade'. It also provided the control variables 'Year', 'State', 'Heat Content Coal', 'Heat Content Gas', and 'Sulfur Content Coal'.

Federal Energy Regulatory Commission (FERC) Form 1 ('Electric Utility Annual Report') provided data on labor (average number of employees), capital (sum of the annual cost of land, structures, and equipment), and annual electrical generation, as well as the age of the plant ('Age Constructed') and plant generation capacity ('Total Capacity').

The 1994 SO_2 and NO_x emissions data are estimated from the Department of Energy.[3] From 1995 onwards, continuous emissions monitoring (CEM) systems were installed in power plants and emissions were measured directly by the Environmental Protection Agency (EPA).[4] A final data source was the EIA Clean Air Act database, from which we collected information to create the 'Phase1' dummy variable.

When calculating the DEA scores for both 'with pollution as output' and 'without pollution as output' scenarios, two plant-years for the coal datasets and 13 for the gas datasets were noted as infeasible linear programming cases and were removed. In addition, twenty-two plant-years in the coal datasets and 78 in the gas datasets obtained DEA scores greater than 1.0 and were also removed.[5] The two coal datasets subsequently have a total of 1273 plant-years representing 159 unique plants while the gas datasets have a total of 1136 plant-years representing 171 unique plants. Although both datasets cover an eleven year period from 1994–2004, data is not available for every plant in every year.

Table 3
Expected signs for regressors.

Variable	Expected sign (DEA with pollution, coal and gas)	Expected sign (DEA w/out pollution, coal and gas)
Regulation variables		
SO_2 regulations (dummy and level variables for SO_2 Limit, Lbs SO_2/h, Pct sulfur, PPM SO_2)	–	+
NO_x regulations (dummy and level variables for NO_x Limit, Lbs NO_x/h, PPM NO_x, NO_x ambient)	–	+
No SO_2 regulation	+	–
No NO_x regulation	+	–
Phase 1 (coal only)	+	+
SO_2 trade (coal only)	–	+
Control variables		
Year	–	–
State	varied	varied
Age constructed	+	+
Total capacity	–	–
Switch fuel	–	–
FERC drop	–	–
Heat content coal (coal only)	–	–
Sulfur content coal (coal only)	+	–
Heat content gas (gas only)	–	–

3.6. Expectations

Table 3 outlines our expected TOBIT analysis results. Because we inverted the DEA score, a *negative* coefficient indicates that the variable is associated with increased efficiency or decreased inefficiency. We expect regressor signs to be the same for gas and coal plants, but different depending on whether or not the DEA score takes into account pollution outputs.

We expect that more stringent regulation levels for SO_2 and NO_x will be associated with *less* efficiency when the DEA score accounts only for electrical generation. When the DEA score takes into account pollution, greater stringency will lead to *greater* efficiency if the benefits of reduced emissions outweigh the costs of reducing these emissions. This applies both to the presence and level of SO_2 and NO_x regulations (i.e., 'dummy' and 'level' variables). Conversely, a lack of SO_2 and NO_x regulations should be associated with *less* efficiency when the DEA takes into account pollution, but *greater* efficiency when it does not. We assume that when firms do not need to pay for pollution abatement, they will produce more electricity.

Since 'Phase1' indicates plants with the dirtiest (and often oldest) boilers, we expect this variable to be associated with less

[3] We thank Carl Pasurka, Jr. of the US-EPA for this 1994 data and for his expert assistance in assembling the rest of the emissions data.

[4] We accessed these emissions data from the US-EPA website: http://cfpub.epa.gov/gdm/index.cfm?fuseaction=emissions.wizard.

[5] In many applications of DEA, researchers have reported scores greater than 1 where they are referred to as "superefficient" firms (Dexter et al., 2008). This occurs because of scaling problems that push values beyond the DEA frontier. For our purposes we have decided that such firms represent a special class and they are eliminated from the analysis.

efficiency under either measure. We expect that plants will be, on average, more efficient after large-scale permit-trading begins as long as the efficiency measure takes into account pollution. When the efficiency measure is based only on electrical generation, we expect plants to be less efficient, on average, after the start of large-scale permit trading, as trading coincides with the need to further reduce SO_2 emissions at these plants.

Regarding control variables, we expect that plants will become more efficient over time, due to technological improvement and increasingly widespread use of market-based mechanisms for regulation. The effect of 'State' is expected to vary depending on the state and region of the country. It is expected that older coal plants will be less efficient due to older technology and higher emissions, and that plants with greater generation capacity will be more efficient because of their economy of scale. Plants able to switch their boilers from 95% of one fuel to 95% of another are highly adaptable, so we expect them to be more efficient. Also, we expect plants that are eventually privatized to be more efficient, assuming that private companies would want to invest in more efficient plants. We expect plants using higher heat-content fuel to be more efficient under either DEA measure. When using the DEA measure that includes pollution as a negative output, we expect that plants using higher sulfur-content coal will be less efficient. We expect the opposite when excluding pollution from the efficiency measure, since the expense of purchasing lower sulfur fuel will not be offset by efficiency gains from pollution abatement.

Table 4
Basic descriptive statistics on the DEA measure.

		N	DEA mean (std. dev.)
Coal plants	DEA w/pollution	1273	0.816 (0.156)
	DEA w/out pollution	1273	0.792 (0.153)
Gas plants	DEA w/pollution	1136	0.559 (0.230)
	DEA w/out pollution	1136	0.529 (0.223)

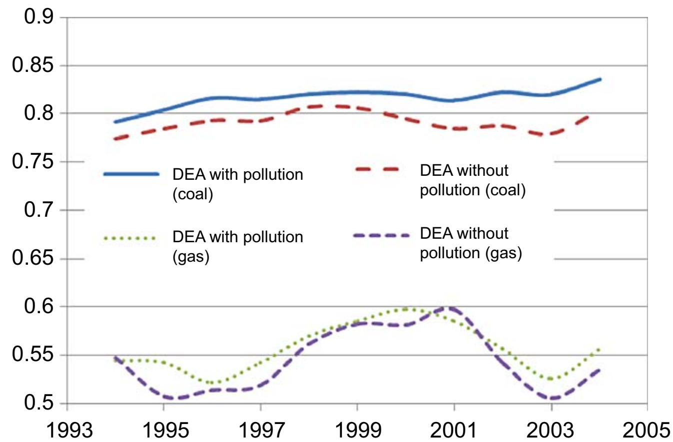

Fig. 1. DEA scores by fuel type and DEA measure (1994–2004).

4. Results and discussion

4.1. Descriptive statistics

Table 4 exhibits basic descriptive statistics on the DEA measure. Higher scores indicate greater efficiency (or reduced inefficiency) in using inputs to generate electricity or reduce pollution. It is important to emphasize that the DEA is a *relative* measure that determines the technical efficiency of each plant-year relative to a 'best practice' frontier, which itself is based on all plant-years in the analysis. As expected, mean efficiencies are higher for plant-years when the DEA analysis includes pollution as a negative output, compared to when pollution is excluded. This occurs because the DEA measure without pollution captures the costs of reducing pollution, in terms of greater input use, but not the benefits of lower pollution.[6] Mean efficiencies are also higher for coal plant-years than gas plant-years. However, since DEA is a relative measure, and gas and coal plant DEAs were calculated separately, no interpretation should be given to this difference.

Fig. 1 shows mean DEA scores over the years 1994–2004. When pollution is included in the measure, coal plants appear more efficient over time, generally increasing by small increments every year. When pollution is not included, coal plants experience a dip starting in 1999. This supports our expectation that increasingly stringent regulation over time has simultaneously depressed electrical productivity and improved environmental performance.

Gas plants appear more efficient over time from 1998 to 2001 but afterwards experience a drop in efficiency. It is important to note that our sample size drops off starting in 2002, especially for gas plants. This could be due to increased privatization which would drop a plant out of the FERC dataset, eliminating our ability to calculate a DEA score. We assume that more efficient plants are more likely to be acquired by private firms.

Table 5 indicates regional variation in DEA score. There appears to be significant regional variation, although speculation on the reasons is not part of this study. We control for this variation in the TOBIT analysis by including state variables.

We also looked at the change in DEA score for individual plants after they initiated any type of SO_2 or NO_x regulation. For plants that first become regulated during our sample time period, we compare the DEA score in the first year with regulation to the DEA score in the previous year. This one-year lagged DEA captures the immediate effect of new regulations on productivity, when the effects are expected to be strongest (after two or more years we expect plants will have adjusted to the requirements). Tables 6a and 6b compare this difference between the current and lagged DEA for newly regulated plants to the difference for plant years in which there was no change in regulations.

The data in Table 6a suggest that, when pollution is included in the efficiency measure, the efficiency of individual coal plants is not affected by the initiation of NO_x regulations. Although there is an increase in the average coal plant's DEA score after NO_x regulations are initiated (+0.003), there is a similar increase that occurs with no regulatory change (+0.002). When pollution is excluded from the DEA efficiency measure, however, plant efficiency appears to be negatively affected by the initiation of NO_x regulation (−0.006), compared to the average annual increase in DEA score when there is no regulatory change (+0.001). It is not possible to look at the effect of SO_2 regulations on coal plants using this method, since there are no coal plants without SO_2 regulations in our dataset.

For gas plants, there are too few plant-years (5) in which SO_2 regulations were initiated – from a base point of no SO_2 regulations – to make any determinations (see Table 6b). The data on NO_x suggest that, when pollution is included in the efficiency measure, the initiation of NO_x regulations is associated with greater efficiency (+0.021), compared to plant-years without

[6] One anonymous reviewer rightly pointed out that mean DEA scores are quite similar whether or not pollution is included in the DEA measure. This indicates that the productivity component (i.e. electrical generation per unit input) has a large influence on our efficiency measure, but does not negate the importance of including pollution abatement.

Table 5
Mean DEA scores by region[a].

Region	Coal (w/pollution)		Coal (w/o pollution)		Region	Gas (w/pollution)		Gas (w/o pollution)	
	N	Mean (std. dev.)	*N*	Mean (std. dev.)		*N*	Mean (std. dev.)	*N*	Mean (std. dev.)
New England	23	0.926 (0.113)	23	0.907 (0.118)	Southeast	191	0.636 (0.203)	191	0.626 (0.232)
Midwest	468	0.835 (0.128)	468	0.804 (0.122)	West-south central	469	0.622 (0.219)	469	0.622 (0.234)
Southeast	489	0.830 (0.134)	489	0.818 (0.138)	Pacific	63	0.600 (0.251)	63	0.474 (0.239)
Midatlantic	99	0.773 (0.199)	99	0.760 (0.195)	Mountain	110	0.536 (0.208)	110	0.533 (0.207)
Mountain	79	0.764 (0.171)	79	0.703 (0.151)	New England	16	0.448 (0.146)	16	0.426 (0.145)
West-south central	98	0.742 (0.228)	98	0.707 (0.218)	Midatlantic	101	0.435 (0.247)	101	0.395 (0.230)
Pacific	17	0.680 (0.217)	17	0.668 (0.209)	Midwest	186	0.397 (0.161)	186	0.392 (0.169)

[a] Regions are modified from Census Bureau "divisions". States included in each region are: New England: RI, MA, VT, NH, ME, CT; Midatlantic: MD, DE, NJ, NY, PA; Southeast: KY, TN, MS, AL, GA, FL, SC, NC, VA, WV; Midwest: ND, SD, NE, KS, MO, IA, MN, WI, IL, IN, MI, OH; West-southcentral: AR, LA, TX. OK; Mountain: MT, ID, WY, NV, UT, CO, AZ, NM; Pacific: WA, OR, CA.

Table 6a
Change in DEA score after regulations are initiated for coal plants.

Coal Plants	*N*	w/pollution in DEA measure: mean (std. dev.)			*N*	w/out pollution in DEA measure: mean (std. dev.)		
		DEA	Lagged DEA	Change		DEA	Lagged DEA	Change
SO_2 regs initiated	0	–	–	–	0	–	–	–
No change in SO_2 regs	1071	0.816 (0.156)	0.814 (0.154)	0.002 (0.066)	1071	0.791 (0.154)	0.791 (0.151)	0.000 (0.065)
NO_x regs initiated	49	0.836 (0.109)	0.832 (0.120)	0.003 (0.068)	49	0.813 (0.116)	0.820 (0.117)	−0.006 (0.076)
No change in NO_x regs	1022	0.815 (0.158)	0.813 (0.155)	0.002 (0.066)	1022	0.790 (0.156)	0.789 (0.153)	0.001 (0.065)

Table 6b
Change in DEA score after regulations are initiated for gas plants.

Gas plants	*N*	w/pollution in DEA measure: mean (std. dev.)			*N*	w/out pollution in DEA measure: mean (std. dev.)		
		DEA	Lagged DEA	Change		DEA	Lagged DEA	Change
SO_2 regs initiated	5	0.735 (0.274)	0.777 (0.227)	−0.041 (0.100)	5	0.706 (0.194)	0.704 (0.174)	0.002 (0.129)
no change in SO_2 regs	874	0.552 (0.220)	0.552 (0.218)	−0.000 (0.135)	874	0.521 (0.215)	0.521 (0.213)	−0.000 (0.125)
NO_x regs initiated	26	0.475 (0.218)	0.454 (0.218)	0.021 (0.167)	26	0.431 (0.171)	0.442 (0.195)	−0.011 (0.140)
no change in NO_x regs	853	0.555 (0.221)	0.556 (0.218)	−0.001 (0.134)	853	0.525 (0.215)	0.525 (0.213)	0.000 (0.125)

Table 7a
Descriptive statistics for dependent variables in TOBIT.

Parameter	Coal plants			Gas plants		
	Mean (std. dev.)	Min value	Max value	Mean (std. dev.)	Min value	Max value
1/DEA score (with pollution)	1.312 (0.559)	1.000	9.647	2.264 (1.477)	1.000	14.158
1/DEA score (without pollution)	1.353 (0.565)	1.000	9.646	2.396 (1.528)	1.000	14.158

a regulatory change (−0.001). The effect is the opposite when the only output in the DEA is electricity generation. The implication is that NO_x regulation improves efficiency when pollution is accounted for the efficiency measure, but decreases efficiency defined in terms of electrical generation only.

4.2. TOBIT regression descriptives

Table 7a exhibits descriptive data for variables used in the TOBIT regressions. Listed first is the dependent variable (1/DEA) in its two formulations—with and without pollution outputs. Table 7b lists the dummy and level regulation variables as well as all control variables except state-fixed effects.

For TOBIT analyses on the coal dataset, the base cases for regulation dummy variables were defined as 'No NO_x Regulation' for NO_x and 'SO_2 Limit' for SO_2. Therefore, the regression coefficient for NO_x dummy variables indicates the effect of that regulation type versus an absence of NO_x regulations. The coefficients for SO_2 regulation dummies indicate the effect of that regulation type compared to the effect of the 'SO_2 Limit' regulation. We were not able to use 'No SO_2 Regulation' as a base case because there were only two plant-years in this category (and, in fact, this variable and its two cases were deleted). For the gas dataset, base cases for regulation dummy variables were 'No SO_2 regulation' for SO_2 and 'No NO_x Regulation' for NO_x, so the regression coefficients indicate the effect of each type versus no regulation.

Table 7b
Descriptive statistics for independent variables in TOBIT.

Parameter	Coal plants			Gas plants		
	Mean (std. dev.)	Min value	Max value	Mean (std. dev.)	Min value	Max value
Regulation variables						
SO_2 limit (dummy)	0.822 (0.382)	0	1	0.384 (0.487)	0	1
SO_2 limit (level)	0.604 (1.066)	0	10.000	0.263 (0.589)	0	7.376
Pct sulfur (dummy)	0.049 (0.217)	0	1	0.107 (0.310)	0	1
Pct sulfur (level)	0.010 (0.053)	0	0.505	0.099 (0.406)	0	3.333
PPM SO_2 (dummy)	0.049 (0.217)	0	1	0.266 (0.442)	0	1
PPM SO_2 (level)	0.019 (0.253)	0	4.000	0.001 (0.010)	0	0.333
NO_x limit (dummy)	0.666 (0.472)	0	1	0.385 (0.487)	0	1
NO_x limit (level)	1.098 (1.586)	0	22.222	1.094 (2.620)	0	50.000
PPM NO_x (dummy)	0.016 (0.127)	0	1	0.047 (0.211)	0	1
PPM NO_x (level)	0.037 (0.295)	0	3.125	0.004 (0.076)	0	2.5
NO_x ambient (dummy)	0	0	0	0.047 (0.211)	0	1
NO_x ambient (level)	0	0	0	0.933 (4.212)	0	20
Lbs SO_2/h (dummy)	0.077 (0.267)	0	1	0.071 (0.257)	0	1
Lbs SO_2/h (level)	0.004 (0.039)	0	0.541	0.002 (0.028)	0	0.444
Lbs NO_x/h (dummy)	0.014 (0.118)	0	1	0.033 (0.178)	0	1
Lbs NO_x/h (level)	0.000 (0.000)	0	0.001	0.000 (0.000)	0	0.003
No NO_x regulation	0.294 (0.456)	0	1	0.479 (0.500)	0	1
No SO_2 regulation	0	0	0	0.093 (0.291)	0	1
SO_2 trade (coal only)	0.407 (0.491)	0	1	n/a	n/a	n/a
Phase 1 (coal only)	0.315 (0.465)	0	1	n/a	n/a	n/a
Control variables						
Year	1998.72 (3.070)	1994	2004	1998.45 (2.953)	1994	2004
Age constructed	35.971 (16.430)	0	86	43.453 (13.723)	0	97
Total capacity	0.873 (0.742)	0.060	3.499	0.620 (0.510)	0.071	2.822
Heat content coal	11.077 (2.202)	5.197	25.171	n/a	n/a	n/a
Heat content gas	n/a	n/a	n/a	1.010 (0.049)	0.450	1.494
Sulfur content coal	1.169 (0.841)	0.061	6.003	n/a	n/a	n/a
FERC drop	0.013 (0.115)	0	1	0.345 (0.476)	0	1
Switch fuel	0.015 (0.121)	0	1	0.024 (0.152)	0	1

Table 8
Tobit regression results (results from regulation variables comprising $<10\%$ of cases are omitted).

Parameter	Coal plants				Gas plants			
	DEA w/pollution ($N = 1273$)		DEA w/out pollution ($N = 1273$)		DEA w/pollution ($N = 1136$)		DEA w/out pollution ($N = 1136$)	
	Coeff (s.e)	Marginal effect	Coeff (s.e.)	Marginal effect	Coeff (s.e.)	Marginal effect	Coeff (s.e.)	Marginal effect
Regulation variables								
Dummy SO_2 limit	Base case for SO_2 regulation types	-0.678^{**} (0.300)	−0.535	-0.615^{**} (0.302)	−0.500			
SO_2 limit	0.042^{**} (0.016)	0.028	0.072^{**} (0.015)	0.052	−0.083 (0.103)	−0.065	−0.081 (0.104)	−0.066
Dummy NO_x limit	0.054 (0.043)	0.037	0.068 (0.041)	0.048	0.289^{**} (0.121)	0.228	0.314^{**} (0.122)	0.255
NO_x limit	−0.007 (0.012)	−0.004	−0.008 (0.114)	−0.006	0.009 (0.018)	0.007	0.017 (0.018)	0.014
Dummy pct SO_2					0.214 (0.335)	0.169	0.224 (0.339)	0.182
Pct SO_2					−0.239 (0.151)	−0.188	−0.189 (0.153)	−0.154
Dummy PPM SO_2					0.102 (0.170)	0.081	0.038 (0.171)	0.031
PPM SO_2					207.7^{**} (26.6)	163.8	221.2^{**} (26.8)	179.7
SO_2 trade	0.074 (0.052)	0.050	0.077 (0.050)	0.055				
Phase 1	-0.086^{**} (0.040)	−0.058	-0.091^{**} (0.039)	−0.065				
Control variables								
Year	−0.010 (0.009)	−0.007	−0.005 (0.008)	−0.004	-0.030^{*} (0.016)	−0.024	-0.036^{**} (0.016)	−0.029
Age constructed	-0.007^{**} (0.001)	−0.005	-0.007^{**} (0.001)	−0.005	0.004 (0.004)	0.003	0.004 (0.004)	0.003
Total capacity	-0.168^{**} (0.023)	−0.114	-0.153^{**} (0.022)	−0.110	0.060 (0.100)	0.047	0.052 (0.101)	0.042
Heat content coal	0.029^{**} (0.009)	0.020	0.040^{**} (0.009)	0.029				
Heat content gas					−0.361 (0.923)	−0.284	−0.386 (0.934)	−0.313
Sulfur content coal	0.136^{**} (0.024)	0.092	0.130^{**} (0.023)	0.093				
FERC drop	−0.141 (0.126)	−0.095	−0.128 (0.121)	−0.092	0.137 (0.143)	0.108	0.131 (0.144)	0.106
Switch fuel	−0.085 (0.123)	−0.057	0.115 (0.116)	0.083	−0.448 (0.323)	−0.353	−0.484 (0.327)	−0.393

** Significant at $p<.05$
* Significant at $p<.10$

4.3. TOBIT regression results

TOBIT analysis results are shown in Table 8. Because we used an inverted DEA score as our dependent variable, a negative coefficient indicates reduced inefficiency, or increased efficiency.

4.3.1. Coal-fired plants

As expected, coal plants with greater capacities tend to be more efficient—on average, a one standard deviation increase in capacity (i.e., 742 kilowatts) is associated with a 6.5% increase in efficiency when pollution is included in the DEA and a 6.1% increase when pollution is excluded.[7] Older plants tend to be *more* efficient, with a one standard deviation increase in the age of the plant (i.e., 16.4 years) associated with an average efficiency gain of 6.3% when the DEA includes pollution and a 6.1% gain when the DEA excludes pollution.[8] Also as expected, higher sulfur content coal is associated with reduced efficiency (a 5.9% or 5.8% decrease in average efficiency, respectively, for the DEA with and without pollution). However, our other fuel quality measure, heat content of coal, was associated with a 3.4% or 4.7% *decrease* in average efficiency, respectively, for the DEA with and without pollution. Collinearity with sulfur content does not appear to explain this unexpected finding.[9] Interestingly, the effects of control variables on efficiency – at least those that are statistically significant – are very similar whether or not pollution is included in the DEA measure.

Regarding regulation effects, participation in phase 1 of the Acid Rain Program is associated with *increased* efficiency (a 4.4% or 4.8% increase in an average efficiency, respectively, for the DEA with and without pollution). Phase 1 allowed a small number of the dirtiest coal plants to begin SO_2 permit trading before large-scale permit trading began. This finding contradicts our expectation that 'dirty' boilers would hamper plant efficiency. Instead, it suggests that early trading allowed these plants to have efficiency gains over non-trading plants that still faced traditional command-and-control regulations. This finding holds even when pollution is excluded from the DEA measure, indicating that efficiency gains for 'Phase1' plants encompass electrical generation as well as pollution abatement. Interestingly, the 'SO_2 Trade' variable is not significant, indicating that it was the small scale, early permit trading, rather than large-scale implementation of the market-based policy, that gave plants a competitive advantage.

Dummy regulation variables for SO_2 are not informative in the coal regression since the base case is the 'SO_2 Limit' dummy. However, the level variable for 'SO_2 Limit' is positive and significant across both DEA measures, indicating that more stringent 'SO_2 limit' regulations *decrease* coal plant efficiency. The magnitudes translate to a 2.3% or 4.1% decrease in average efficiency, respectively, for the DEA with and without pollution. It is important to note that, when the DEA measure includes pollution outputs, the dampening effect of the 'SO_2 Limit' regulation on efficiency is reduced by 40%. This suggests that the 'SO_2 Limit' regulation helps to reduce SO_2 pollution levels, but this reduction is not significant enough to overcome productivity losses.

For coal-power plants, there appears to be no significant effect of NO_x regulations on our integrated measure of efficiency.

4.3.2. Gas-fired plants

Gas plants appear to improve their efficiency over time (as expected), but all other control variables showed no significant effect. Turning to regulation, we find that the presence of the 'SO_2 Limit' regulation is associated with a large increase in efficiency (a 24% or 21% increase in average efficiency, respectively, for the DEA with and without pollution). This suggests that the benefits of reduced SO_2 emissions exceed the costs of reducing these emissions from gas plants. In contrast, the presence of the 'NO_x Limit' regulation is associated with *decreased* efficiency (a 10% or 11% decrease in average efficiency, respectively, for the DEA with and without pollution). As natural gas plants are typically cleaner than coal-fired plants, it may be that the additional benefits from reduced NO_x pollution are small relative to the costs of NO_x pollution control. Results are similar regardless of which efficiency measure is used; however, the exclusion of pollution abatement does, as expected, overestimate the negative impact of NO_x regulations and underestimate the positive impact of SO_2 regulations. The regulation level variables for 'SO_2 Limit' and 'NO_x Limit' are not significant in the TOBIT, indicating that it is the presence or absence of these regulations – rather than their stringency – that affects gas plants' efficiency.[10]

5. Conclusions

The purpose of this research was twofold. First, we developed an efficiency measure for US power plants that accounts for both economic goods and environmental harm, in the form of electrical generation and the emissions of multiple pollutants. Second, we examined the effect of air quality regulations on this integrated efficiency measure by using the measure as a dependent variable in TOBIT analyses.

We found DEA to be a useful and adaptable tool. It provided a certain level of objectivity by not requiring us to assign values to productivity versus pollution abatement, or to SO_2 versus NO_x abatement. A disadvantage was that, when using only the integrated DEA measure, we could not distinguish the cause of variation. Was an increase in DEA score associated with increased electrical generation, decreased pollution, or both? Our response was to compare results using the integrated measure to results using a 'single output' measure accounting only for electrical generation. Other approaches may be used to complement our results. Separate regressions on the three output measures may shed further light on how regulation affects the level of each output individually. There are also alternative dependent variables that could be used to produce results in comparison to those we achieved through DEA (see, for example, Tyteca, 1996). This use of multiple indicators is a good way to ensure the robustness of the results (Färe et al., 1996).

[7] The percent change in efficiency associated with each independent variable is calculated from the marginal effects in Table 8.

[8] While an important control, the age variable has no direct interpretation in this study. First, capital cost data utilized to calculate the DEA are in nominal units. We are unable to adjust the figures provided in the FERC survey for inflation, as we do not know the years in which capital investments were made. However, we expect that investment in older plants occurred before investment in newer plants. Second, age controls for differences in the age of equipment. Age is based on the year of original construction, which indicates the age of the plant as a whole. While boilers at older plants have had technology updates since initial construction, data on when these updates occurred are not aggregated to the plant level.

[9] We checked for collinearity between the heat content and sulfur content variables, which could reduce the precision of the estimates. Although they are correlated, the correlation is not so high as to present a problem in the TOBIT (Pearson's correlation coefficient = 0.39, $p<0.0001$).

[10] The apparent significance of the 'PPM SO_2' regulation level variable is likely a fixed effect of the small number of states that apply this regulation; thus we do not emphasize this result. Plants covered by the 'PPM SO_2' regulation are primarily located in Texas (64%), followed by Louisiana (22%) and California (14%).

Our findings regarding the efficiency effects of regulations were mixed. More stringent SO_2 regulations have a negative effect on coal plant efficiency – although this becomes less negative after accounting for pollution abatement benefits – while the presence of SO_2 regulations positively affects gas plant efficiency. The explanation for this difference may be the low sulfur content of natural gas, which makes SO_2 regulations comparatively less costly for gas plants. Conversely, NO_x regulations appear to have no significant effect on coal plant efficiency but a negative effect on gas plant efficiency, although accounting for the benefits of pollution abatement lessened the negative effect. Compared to SO_2 regulations, NO_x regulations are usually less stringent and less costly to comply with, particularly for coal plants. Most coal plants face NO_x regulations that can be met using low-cost modifications, such as low-NO_x burners, rather than costlier technologies such as selective catalytic reduction (SCR). For gas plants, on the other hand, it may be that the lower initial NO_x emissions make the benefits of additional NO_x regulations too small to justify the costs of regulation.

We were surprised that coefficients for regulation variables were in the same direction and similar in magnitude whether or not pollution was included in the DEA measure. For regulations associated with decreased efficiency, this means that productivity losses associated with compliance outweighed the benefits of reduced pollution. In practical terms, this means that regulators and regulated plants need to consider how to reduce compliance costs for certain costly regulations or find a way to properly account for the benefits of regulation. Perhaps our measure, which assigns no special weight to pollution reduction, understates its advantages in relation to production.

On the other hand, the presence of the 'SO_2 Limit' regulation in gas plants is associated with an efficiency gain *even when pollution is not included in the DEA*. This suggests that when compliance costs are relatively low, the compliance effort has a positive effect on productivity (as well as pollution), perhaps by identifying and correcting other inefficiencies.

Another key finding was the advantage gained by plants participating in Phase 1 of the Acid Rain Program. This supports the finding of Färe et al. (2006, p. 259), who found that plants participating in Phase I showed 'dramatic improvement' in their Environmental Performance Index during their year of participation. More broadly, it supports the literature on market-based mechanisms, which argues that permit-trading leverages the free market to correct inefficiencies in command-and-control regulations. We found that the greatest advantage came from the exclusive permit trading market for Phase 1, whereas large-scale permit trading showed no effect. This makes sense since our DEA is a *relative* measure; thus, being part of a small number of plants with a competitive advantage would translate to a higher score.

Finally, and most broadly, our results highlight the importance of thinking about firm efficiency in terms of *multiple* positive and negative outputs rather than a uni-dimensional measure of financial performance when evaluating the combined social and economic impacts of environmental regulations. As environmental regulations evolve to capture diverse economic and environmental goals, scholars must explore new ways to incorporate these goals into empirical analysis and evaluation. Environmental and social values should be *part of* a rigorous evaluation of regulation and other policies, rather than secondary concerns. As time progresses and regulations change, we hope that future research will make use of additional data to expand upon these results.

References

Aiken, D.V., Pasurka Jr., C.A., 2003. Adjusting the measurement of US manufacturing productivity for air pollution emissions control. Resource and Energy Economics 25, 329–351.

Berman, E., Bui, L.T.M., 2001. Environmental regulation and productivity: evidence from oil refineries. The Review of Economics and Statistics 83 (3), 498–510.

Boyd, G.A., McClelland, J.D., 1999. The impact of environmental constraints on productivity improvement in integrated paper plants. Journal of Environmental Economics and Management 38, 121–142.

Boyd, G.A., Tolley, G., Pang, J., 2002. Plant level productivity, efficiency, and environmental performance of the container glass industry. Environmental and Resource Economics 23, 29–43.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. Journal of Environmental Management 51, 229–240.

Cole, MA., Elliott, R.J.R., Shimamoto, K., 2005. Industrial characteristics, environmental regulations and air pollution: an analysis of the UK manufacturing sector. Journal of Environmental Economics and Management 50, 121–143.

Dexter, F., O'Neill, L., Xin, L., Ledolter. J., 2008. Sensitivity of super-efficient data envelopment analysis results to individual decision-making units: an example of surgical workload by specialty. Health Care Management Science, Online Publication, 28 February, 2009.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 1989. The effect of environmental regulations on the efficiency of electric utilities: 1969 vs. 1975. Applied Economics 21, 225–235.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. Journal of Regional Science 413, 381–409.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2006. Social responsibility: US power plants 1985–1998. Journal of Productivity Analysis 26, 259–267.

Färe, R., Grosskopf, S., Pasurka Jr., C.A., 2007. Pollution abatement activities and traditional productivity. Ecological Economics 62, 673–682.

Färe, R., Grosskopf, S., Tyteca, D., 1996. An activity analysis model of the environmental performance of firms—application to fossil-fuel-fired electric utilities. Ecological Economics 18, 161–175.

Färe, R., Grosskopf, S., Hernandez-Sancho, F., 2004. Environmental performance: an index number approach. Resource and Energy Economics 26, 343–352.

Gollop, F.M., Roberts, M.J., 1983. Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. Journal of Political Economy 91 (4), 654–674.

Greenstone, M., 2002. The impacts of environmental regulations on industrial activity: evidence from the 1970 and 1977 clean air amendments and the census of manufactures. Journal of Political Economy 110, 1175–1219.

Greenstone, M., 2004. Did the clean air act cause the remarkable decline in sulfur dioxide concentrations? Journal of Environmental Economics and Management 47, 585–611.

Hollenbeck, K., 1979. The employment and earnings impacts of the regulation of stationary source air pollution. Journal of Environmental Economics and Management 6, 208–221.

Lam, P., Shiu, A., 2004. Efficiency and productivity of China's thermal power generation. Review of Industrial Organization 24, 73–93.

Majumdar, S.K., Marcus, A.A., 2001. Rules versus discretion: the productivity consequences of flexible regulation. Academy of Management Journal 441, 170–179.

Murty, M., Kumar, S., Dhavala, K.K., 2007. Measuring environmental efficiency of industry: a case study of thermal power generation in India. Environmental and Resource Economics 38 (1), 31–50.

Olatubi, W.O., Dismukes, D.E., 2000. A data envelopment analysis of the levels and determinants of coal-fired electric power generation performance. Utilities Policy 9, 47–59.

Ringquist, E., 1993. Does Regulation matter? Evaluating the effects of state air pollution control programs. Journal of Politics 554, 1022–1045.

Shadbegian, R.J., Gray, W.B., 2003. What determines environmental performance at paper mills? The roles of abatement spending, regulation, and efficiency. Topics in Economic Analysis & Policy, 3(1), Article 15.

Shadbegian, R.J., Gray, W.B., 2005. Pollution abatement expenditures and plant-level productivity: a production function approach. Ecological Economics 54, 196–208.

Shadbegian, R.J., Gray, W.B., 2006. Assessing multi-dimensional performance: environmental and economic outcomes. Journal of Productivity Analysis 26, 213–234.

Smith, J.B., Sims, W.A., 1985. The impact of pollution charges on productivity growth in Canadian brewing. The RAND Journal of Economics 163, 410–423.

Tyteca, D., 1996. On the measurement of the environmental performance of firms—a literature review and a productive efficiency perspective. Journal of Environmental Management 46, 281–308.

Tyteca, D., 1997. Linear programming models for the measurement of environmental performance of firms-concepts and empirical results. Journal of Productivity Analysis 8, 183–197.