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Environmental Regulations and Allocative Efficiency: An Application to Coal-to-Gas Substitution in the U.S. Electricity Sector

by

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Abstract: The environmental economics literature has for a long time been occupied with the relationships between environmental regulations, technical efficiency, and productivity growth. This paper extends this discussion by taking up environmental regulations' implications for allocative efficiency. It establishes a model framework that allows disentangling managerial and regulatory induced allocative efficiencies, and utilizes Data Envelopment Analysis to a sample of 67 coal-to-gas substituting power plants observed from 2002 to 2008 to calculate Nerlovian profit efficiencies and their technical and allocative efficiency components. The empirical results illustrate that failing to control for environmental regulations leads to overestimation of managerial allocative efficiencies by ignoring compliance costs. Marginal abatement cost estimates that are in line with allowance prices for NO_x and SO_2 are further obtained.

JEL-codes: *D200; Q520; C610; Q400*

Keywords: *Polluting technologies*; *Materials balance condition; Nerlovian efficiency; Data Envelopment Analysis*

1. INTRODUCTION

The environmental economics literature has for a long time been occupied with the relationships between environmental regulations, technical efficiency, and productivity growth; see e.g. Porter and van der Linde (1995) and Palmer et al. (1995) for a discussion. Several recent papers, e.g. Chung et al. (1997), Färe et al. (2001, 2007), and Ball et al. (2005), reconsider the implications of pollution reduction for technical efficiency and technical change, commenting on earlier papers on the relationship between environmental regulations and traditional measures of productivity (see Jaffe et al. (1995) for an overview). A key finding is that the earlier studies consider inputs applied for pollution control purposes unproductive because the corresponding emission reductions are ignored. Chung et al., Färe et al., and Ball et al. attempt to address this measurement problem by including pollutants, thus reflecting pollution control efforts, in the production model.

Rødseth (2014) acknowledges that regulatory induced measurement biases for technical efficiencies are encountered when pollutants are reduced by pollution control, but points out that it is only one of many options which producers have for complying with environmental regulations. Whenever other compliance strategies are preferred to pollution control, the above-proposed corrections of measurement biases for technical efficiency and productivity growth provide limited insights about the economic implications of environmental regulations. In fact, in their study on U.S. power plants, Färe et al. (2007) were unable to identify significant performance measurement biases related to the plants' emission reductions.

While the emphasis has been on environmental regulations' implications for technical efficiency and productivity growth, a few recent papers (in particular Førsund (2009), Rødseth (2013), and Rødseth and Romstad (2014)) suggest that environmental regulations may also play an important role for allocative efficiency. More specifically, they argue that environmental regulations increase the costs of pollution-generating inputs (e.g., fossil fuels), and that producers who are subject to environmental regulation maximize their profits subject to shadow prices for pollution-generating inputs that differ from the inputs' observed market prices. Profit efficiency comparisons that overlook this aspect ignore the producers' compliance costs and thereby fail to rank them according to their true economic efficiency. The main purpose of this paper is to treat this measurement bias. First, the paper establishes an analytical framework for modeling regulatory induced allocative inefficiencies. Second, the paper evaluates the magnitude of the measurement bias by an empirical application on the U.S. power sector, applying Data Envelopment Analysis (DEA) to a sample comprising 67 coal-to-gas substituting electricity plants. Third, marginal abatement cost estimates that are in line with the allowance prices for sulfur dioxide (SO_2) and nitrogen oxides (NO_x) are obtained based on regulatory pollution constraints.

This paper is comparable to previous papers that have used production analysis to analyze how environmental regulations influence economic efficiency. Brännlund et al. (1995) evaluate how pulp-and-paper plants' profits are affected by existing individual emission quotas, while Brännlund et al. (1998) evaluate potential economic gains from replacing individual quotas by an emissions trading scheme. Transferable quotas have received much interest in environmental production economics, and have recently been treated by Oude Lansink and van der Vlist (2008) and Färe et al. (2013b; 2014) among others. Hampf and Rødseth (2015b) provide a production analysis framework for analyzing the impact of performance standards and emission intensity averaging on profitability.

Moreover, a recent paper by Granderson and Prior (2013) evaluates the impact of environmental and rate-of-return regulations on U.S. power plants' total factor productivity growth. They utilize a Malmquist cost productivity index that allows identifying the impact of allocative efficiency on productivity growth, and find that electric utilities subject to environmental regulation operate less allocative efficient than their non-regulated peers.

An important difference between this study and the reviewed studies (with the exception of Hampf and Rødseth's paper) is that they are based on Färe et al.'s (1989; 2005) model framework, which is a well-known work horse in environmental production analysis. As the axiom of free disposability of inputs is one of its building blocks, Färe et al.'s model assumes that the consumption of inputs can be extended (infinitely) for given good and bad outputs. This paper uses the materials balance principle to show that environmental restrictions impose upper bounds on the use of polluting-generating (i.e., material) inputs, thereby inducing allocative inefficiency from the producer's point of view. Foregone profits because of regulatory-induced (implicit) input restrictions is clearly a relevant measure of compliance costs.

2. THEORY

2.1. ON POLLUTION GENERATION

Ayres and Kneese (1969) demonstrated the fundamental importance of the materials balance condition for the joint production of desirable and undesirable outputs in many conventional production processes. Recently several authors, including Krysiak and Krysiak (2003), Pethig (2003, 2006), Ebert and Welsch (2007), Coelli et al. (2007), Lauwers (2009), Førsund (2009), Rødseth (2013, 2015), Rødseth and Romstad (2014), and Hampf (2014), have considered different ways in which the neoclassical production model can be accommodated to comply with the materials balance condition. The current paper can be considered a contribution to this literature.

The materials balance condition postulates that materials can neither be created nor destroyed, but may change their form. The weight of production inputs, including non-economic inputs such as oxygen, must thereby amount to the weight of the outputs. Material inflows to the production process which are not recuperated in desirable outputs remain as (undesirable) byproducts from the production process.

The materials balance condition can be represented by emission factors rather than material flow coefficients. This is particularly suitable for air pollution emissions, because the oxygen inflow then does not need to be explicitly modeled. The factors provide estimates of the amount of undesirable byproducts released per unit of conventional inputs (e.g., fossil fuels) used, as well as the amount recuperated per unit of desirable outputs produced. Let $x \in \Re_+^N$ denote a vector of inputs, $y \in \Re_+^M$ denote a vector of desirable outputs, and $b \in \Re_+^K$ denote a vector of undesirable byproducts. Let *N* be a $K \times N$ matrix of non-negative input emission factors[1] and *M* be a $K \times M$ matrix of non-negative output

[1] The emission factors are allowed to vary across producers, dependent on the quality of their inputs. For example, there exist various qualities of coal which differ in terms of their sulfur content. Taking into account that inputs are not perfect homogeneous introduces flexibility for the producers, allowing undesirable outputs to be reduced by changing the quality of their inputs.

recuperation factors. The latter refers to the quantities of materials embodied in each unit of the good outputs. The materials balance conditions for the *K* undesirable byproducts are then defined by:

$$b^{uc} = Nx - My \qquad (1)$$

Equation 1 reports *uncontrolled* byproducts.

Producers frequently engage in pollution control activities to "clean up" emissions instead of preventing them from occurring. Pollution control efforts can thus be represented by subtracting $a \in \Re_{+}^{K}$ from equation 1[2]. Note that pollution control transforms the undesirable byproducts into other byproducts rather than making them "dematerialize" or vanish. However, since this paper is concerned with regulatory restricted byproducts, pollution control is viewed as reducing the undesirable byproducts. Emissions remaining after pollution control, b^c, are called *controlled* byproducts:

$$b^{c} = Nx - My - a \qquad (2)$$

The subsequent analysis uses equation 2 as point of departure. For notational convenience, the superscript *c* is omitted in the following.

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[2] See Førsund, F.R., 2009. Good modelling of bad outputs: pollution and multiple-output production. Int Rev Environ Resour Econ 3, 1-38. for a more detailed discussion on pollution control.

2.2. A POLLUTING TECHNOLOGY

The theory presented in this section builds on Rødseth (2013) and Rødseth and Romstad (2014). These studies were in turn influenced by Krysiak and Krysiak (2003), Førsund (2009), and Murty et al. (2012), who propose production models that are composed of multiple sets or production relations. The purpose is to limit the degree of substitutability among desirable and undesirable outputs, and thereby to obtain a production model that is in line with physical constraints on the conversion of inputs into outputs that were explained in section 2.1; see Førsund (2009) and Rødseth and Romstad (2014) for more details. The use of multiple production relations to limit the substitutability among outputs is due to Frisch (1965).

Consider the polluting technology as the intersection of the neo-classical technology, *T1*, and the materials balance conditions, *T2*. The latter are defined by equation 2 (i.e., controlled emissions), which is embodying *K* "production functions" for the pollutants. In this paper, the main objective is to evaluate how environmental regulations restrict production possibilities and thereby influence profits. Unlike the approaches of Førsund (2009) and Murty et al. (2012), the residual-generating technology *T2* is therefore defined by emission *constraints* (i.e., as inequalities) – reflecting that environmental regulations cap emissions – rather than the production functions (i.e., as equalities) for the undesirable outputs. Thus, the emission constrained technology is in (x,y)-space defined by equation 3[3].

[3] The technology set T(b+a) depends on both the emission factors, N and M, and uncontrolled emissions, b+a. This implies that correct notation for the technology set is T(N,M,b+a). N and M are omitted to allow for a simpler notation. This is especially convenient for the profit function in equation 4.

$$
\begin{aligned}
&T(b+a)=T1\cap T2(b+a),\\
&T1=\{(x,y):x\text{ can produce }y\}\\
&T2(b+a)=\{(x,y):Nx-My\le b+a\}
\end{aligned}
\tag{3}
$$

T1 is assumed to be a nonempty, closed, and convex set. No fixed costs, no free lunch, and free disposability of inputs and desirable outputs are assumed to prevail. See Chambers (1988) for a discussion of these properties.

Recently, Färe et al. (2013a) and Hampf (2014) modeled polluting technologies for energy generation that consist of production (i.e., the joint production of electricity and uncontrolled air pollution) and pollution control (i.e., controlled emissions and emission reductions due to end-of-pipe abatement) stages. The model in equation 3 can also be interpreted as a network-type (i.e., multi-stage) model, where the emphasis is on the production stage while the pollution control stage is not modeled in detail. This is achieved by following Førsund (2009), assuming that pollution control is a separate production process and moreover that "pollution control inputs" are not used at the expense of "production inputs". This hypothesis is supported by the empirical analysis of Shadbegian and Gray (2005), who find that "pollution control inputs" contribute little or nothing to intended production. Note that the pollution control technology is not explicitly modeled to avoid problems related to poor accessibility and reliability of data on these activities; cf. the very small samples used by Färe et al. (2013a) and Hampf (2014). Instead, pollution control is treated as a service or an input that producers *can* purchase to reduce their generation of the *K* undesirable byproducts. Hence, the producers face exogenous prices for abatement services[4].

This paper considers compliance costs to arise in the production stage because environmental regulations constraint the consumption of production inputs. While pollution control is viewed as a compliance strategy that possibly lowers these regulatory-induced allocative inefficiency costs, it is only an option, not a necessity, for regulatory compliance. The model in equation 3 is flexible enough to weight the costs of different compliance strategies, and thereby to identify the least costly compliance strategy. Førsund and Strøm (1988) consider input substitution, output reductions, technical change, waste recycling, and end-of-pipe abatement activities as potential compliance strategies. Technical change refers to intertemporal changes to the technology set *T*1, while input substitution and output reductions refer to reallocation of (production) inputs and outputs within *T*1. In particular, input substitution refers to the possibility to substitute inputs with high emission factors (e.g., coal) with inputs with lower emission factors (e.g., natural gas). The two latter compliance strategies (i.e., waste treatment and end-of-pipe abatement) can be labeled pollution control strategies, and thus relate to the pollution control efforts *a* in *T*2.

T2(*b+a*) is the set of inputs and desirable outputs that are consistent with uncontrolled emissions smaller or equal to *b+a*. This set is particularly relevant for modeling how environmental regulations that cap controlled emissions, *b,* influence the producers' input consumption and the intended outputs of the production stage. Clearly, the materials

[4] In terms of structural consequences, it implies that the *K* abatement outputs are assumed non-joint in inputs and that each of the *K* abatement production functions are linear homogenous.

balance principle implies that bounds on emissions must similarly imply bounds on the producers' possible input use and desirable production; c.f. equations 1-2. Thus, for a fixed level of pollution control, *a*, there exists a restricted set of inputs and desirable outputs that are consistent with the regulatory constraints. The access to employing technology *T1* is thus limited by regulatory constraints on emissions, in the sense that $T\left(b+a\right)\subseteq T1$[5].

Recall from equation 2 that pollution control is modeled by subtracting a from the uncontrolled emissions. This means that any increase in pollution control efforts (for a given cap on controlled emissions, *b*) expands the set of feasible inputs and desirable outputs in the production stage, hence generating a trade-off for the producers: Involvement in pollution control may allow them to reach more profitable input-output allocations in *T*1 (i.e., in the production stage). For example, by cleaning up more of their air pollution, electric utilities may consume larger amounts of high-polluting (and cheap) fossil fuels while complying with existing emission quotas. However, pollution control is costly.

Cap and trade regulations offer additional possibilities to change the emission restricted set *T2*. Rather than changing the pollution control output, *a*, they change the level of maximal allowable emissions, *b*. That is, the set *T*2 can be expanded by purchasing emissions allowances, while it is reduced when selling allowances. Pollution control efforts

[5] *T*2(*b*+*a*) can be interpreted as violating free disposability of inputs. Note that my modeling approach thereby resembles the approach of Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C.A., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 71, 90-98., who evaluate the costs of environmental regulations by comparing two technologies in which pollutants are freely and not freely disposable, respectively.

and allowance purchases can be seen as perfect substitutes for the purpose of changing *T*2. In the following, I emphasize the economics of pollution control, but the economics of emissions trading can be laid out accordingly.

The theory of producers with restricted access to the production technology, usually due to cost or revenue constraints, is called indirect production theory (Shephard, 1974). This theory was extended by Lee and Chambers (1986) and Färe et al. (1990) to consider profit maximization when producers face expenditure constraints. Limits to credit may force producers to operate suboptimal, making them appear allocative inefficient when credit constraints are not accounted for. This paper builds on these ideas.

Consider short run profit maximization, where the input vector is partitioned into *V* variable inputs and *F* (quasi)fixed inputs, i.e. $x=(x_v,x_f)$. Let $w \in \Re_{++}^{V}$, $r \in \Re_{++}^{M}$, and $p \in \Re_{+}^{K}$ be vectors of prices for variable inputs, desirable outputs, and pollution control, respectively. Define the short run profit maximization problem for a producer that complies with environmental regulations as:

$$\begin{aligned} \pi\left(r,w,p,x_f,b\right) &= \sup_{x_v,y,a} \left\{ry - wx_v - pa : \left(x,y\right) \in T1, Nx - My \le b + a\right\} \\ &= \sup_{a} \left\{ \sup_{x_v,y} \left\{ry - wx_v : \left(x,y\right) \in T1, Nx - My \le b + a\right\} - pa \right\} \qquad (4) \\ &= \sup_{a} \left\{ \pi^C\left(r,w,x_f,b+a\right) - pa \right\} \end{aligned}$$

π^C represents the emission constrained short run profit function. It defines maximal obtainable profits to prices *r* and *w*, under the *exogenous* emission constraints *b*+*a*. The emission constrained short run profit function is non-decreasing and concave in *a* due to technology T1's properties of free disposability and convexity, which thereby allows a solution to the profit maximization problem from equation 4. This solution is characterized by the level of pollution control that maximizes the difference between the restricted profits and the abatement costs. At this level of pollution control the producer's marginal economic benefits from expanding his/her access to technology *T*1 (i.e., to increase economic gains in the production stage) equal the marginal abatement costs as illustrated by figure 1.

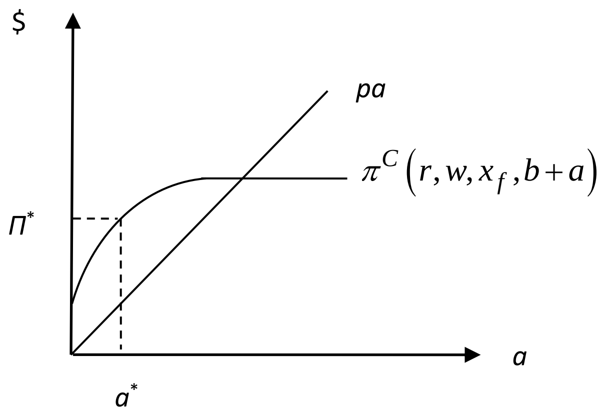

Figure 1: *Emission restricted profit maximization*

In figure 1, the solution to the emission restricted profit problem leads to forgone profits relative to the maximal obtainable profits. The latter is formally defined by the conventional short run profit function:

$$\pi\left(r, w, x_f\right) = \sup_{x_v, y}\left\{ry - wx_v : (x, y) \in T1\right\} \qquad (5)$$

and is represented by the maximum of π^C in figure 1. Define the inequality:

$$\pi\left(r, w, x_f\right) \geq \pi^C\left(r, w, x_f, b+a\right) \tag{6}$$

Following the argument by Färe and Logan (1983), the unrestricted profit function can be retrieved from the restricted profit function by applying the inequality in equation 6:

$$\pi\left(r, w, x_f\right) = \sup_a \left\{\pi^C\left(r, w, x_{f,} b+a\right)\right\} \tag{7}$$

When increasing pollution control, *a*, the set of feasible combinations of inputs and desirable outputs is expanded. By sufficiently expanding the set, the unconstrained profit maximum can be achieved since $T\left(b+a\right) \subseteq T1$.

Assume that the abatement costs in equation 4 are zero. The profit maximization problem for the emission restricted producer is then reduced to:

$$\begin{aligned}\pi\left(r, w, 0, x_f, b\right) &= \sup_a \left\{\pi^C\left(r, w, x_f, b+a\right)\right\} \\ &= \pi\left(r, w, x_f\right)\end{aligned} \tag{8}$$

where the last equality follows from equation 7. Equation 8 shows that the constrained and the unconstrained profit problem coincide when the abatement costs are zero. In this case, the producer employs polluting inputs without facing costs related to their cleanup.

The main insight of the previous discussion is that environmental regulations impose implicit costs on the use of polluting inputs in the production stage, thereby leading to profit losses relative to the conventional profit maximum. A measure of overall efficiency that does not take this into account will consider regulated producers as inefficient, even if they are optimally allocated under their regulatory constraints. The empirical analysis in sections 3 and 4 therefore evaluates the economic impact of regulatory constraints by comparing maximal profits under exogenous emission constraints, π^C, to maximal profits without emission constraints, π. The difference between the two maxima is a measure of abatement costs, and hence a measure of allocative inefficiency attributed to environmental restrictions. The emission restricted profit function, π^C, is estimated under the assumption that the realized level of emissions – and hence pollution control efforts and allowance purchases – solve the maximization problem in equation 4.

2.3. NERLOVIAN PROFIT EFFICIENCY AND THE DIRECTIONAL DISTANCE FUNCTION

The directional distance function and its duality to the profit function from equation 5 were introduced by Chambers et al. (1998). It encompasses all known distance functions as special cases. This is due to the flexibility of selecting the direction in which inputs and outputs are projected to the technology frontier by the choice of the direction vector g=(g_x,g_y) in $\Re_+^N \times \Re_+^M$. Here, the direction vector is set equal to g_f=0 for the (quasi)fixed inputs. The directional distance function is then defined as:

$$\begin{aligned} \vec{D}\left(x, y; -g_v, 0, g_y\right) &= \sup\left\{\beta \in \Re : \left(x_v - \beta g_v, x_f, y + \beta g_y\right) \in T\left(b + a\right)\right\} \\ &= \sup\left\{\beta \in \Re : \left(x_v - \beta g_v, x_f, y + \beta g_y\right) \in T1\right\} \end{aligned} \tag{9}$$

where the last equality follows from $T(b+a) \subseteq T1$ and that the materials balance constraints in $T2(b+a)$ do not prevent contraction of inputs and expansion of desirable outputs. The directional distance function inherits the properties of the parent technology. It satisfies the translation property and is homogeneous of degree minus one in *g*, nondecreasing in x_v, nonincreasing in *y*, and concave in (x_v,y). Under free disposability the directional distance function provides a complete characterization of the underlying technology in the sense that:

$$\vec{D}\left(x, y; -g_v, 0, g_y\right) \geq 0 \text{ if and only if } (x, y) \in T1 \tag{10}$$

i.e., it takes the value 0 if the producer is technical efficient, and a value greater than 0 if not. The short-run unrestricted profit function from equation 5 may thus be defined in terms of the directional distance function:

$$\pi\left(r, w, x_f\right) = \sup_{x_v, y}\left\{ry - wx_v : \vec{D}\left(x, y; -g_v, 0, g_y\right) \geq 0\right\} \tag{11}$$

Chambers et al. (1998) showed that the optimization problem in equation 11 can be written as an unconstrained problem:

$$\pi\left(r, w, x_f\right) \geq ry - wx_v + \left(rg_y + wg_v\right)\vec{D}\left(x, y; -g_v, 0, g_y\right) \tag{12}$$

Rewriting expression 12 and adding allocative inefficiency (*AE*) to secure equality, the Nerlovian profit efficiency and its decomposition into technical and allocative inefficiency is defined:

$$\frac{\pi\left(r, w, x_f\right)-\left[ry-wx_v\right]}{\left(rg_y+wg_v\right)}=\vec{D}\left(x, y;-g_v, 0, g_y\right)+AE \tag{13}$$

which takes the value 0 if the producer is profit efficient, and a value greater than 0 if not. The Nerlovian profit efficiency measure is invariant to proportional price changes due to the normalization (rg_y+wg_v). The normalization allows maximum profits to be zero or negative, which gives the measure an advantage over profit efficiency measures that use maximum profits as normalization. Furthermore, it allows identifying allocative profit inefficiency. This corresponds to the paper's objective; to identify the effect of environmental regulations on allocative efficiency.

Exploiting equation 9, i.e., that the directional distance function defined on *T*(b+a) is equivalent to the directional distance function defined on *T*1, equation 11 can be restated for the emission restricted profit function. Applying equation 12, the Nerlovian profit efficiency for the emission restricted technology is consequently:

$$\frac{\pi^C\left(r, w, x_f, b+a\right)-\left[ry-wx_v\right]}{\left(rg_y+wg_v\right)}=\vec{D}\left(x, y;-g_v, 0, g_y\right)+AE^C \tag{14}$$

By earlier results, $\pi\left(r, w, x_f\right) \geq \pi^C\left(r, w, x_f, b+a\right)$ and the directional distance functions in equations 13 and 14 are equivalent. This means that any difference between the unrestricted and the emission restricted Nerlovian profit efficiencies (*AE* - AE^C) is solely due to induced allocative inefficiency, arising because environmental regulations prevent producers from maximizing profits to the prevailing market prices for inputs and outputs.

3. EMPIRICAL IMPLEMENTATION

3.1. DATA ENVELOPMENT ANALYSIS

Linear programming techniques are used to compute Nerlovian efficiencies for a sample of U.S. power plants that comply with legal restrictions on air pollution. Assume there are *l=(1,..,L)* power plants in the dataset. Each plant uses inputs $x^l = \left(x_1^l,..,x_N^l\right) \in \Re_+^N$ to produce desirable outputs $y^l = \left(y_1^l,..,y_M^l\right) \in \Re_+^M$. The inputs are partitioned into *V* variable inputs and *F* quasifixed inputs, i.e. $x^l = \left(x_v^l, x_f^l\right)$. Let λ^l, *l=(1,..,L),* be the intensity variables. The emission constrained DEA profit problem that maximizes profits under the exogenous emission constraints *b+a* is then defined for plant *l'* as:

$$\pi^C\left(r^{l'}, w^{l'}, x_f^{l'}, b^{l'} + a^{l'}\right) = \max_{y,x_v,\lambda} \sum_{m=1}^{M} r_m^{l'} y_m - \sum_{n=1}^{V} w_n^{l'} x_n : \begin{array}{ll} \sum_{l=1}^{L} \lambda^l y_m^l \geq y_m, & m = 1,....,M \\ \sum_{l=1}^{L} \lambda^l x_n^l \leq x_n, & \text{n} = 1,......,V \\ \sum_{l=1}^{L} \lambda^l x_n^l \leq x_n^{l'}, & \text{n=V+1,...,N} \\ \lambda^l \geq 0, \ \ \text{l} = 1,......,L, & \sum_{l=1}^{L} \lambda^l = 1, \\ \sum_{n=1}^{V} n_{kn}^{l'} x_n + \sum_{n=V+1}^{N} n_{kn}^{l'} x_n^{l'} - \sum_{m=1}^{M} m_{km}^{l'} y_m & \\ \leq b_k^{l'} + a_k^{l'}, & \text{k=1,.......,}K \end{array} \tag{15}$$

Note that both the emission constraints, $b_k^{l'} + a_k^{l'}$, and the emission factors, $\left(n_{kn}^{l'}, m_{kn}^{l'}\right)$, are plant specific. This reflects differences in fuel qualities across plants, which is relevant because fuel types and qualities are among the power plants' key choice variables for complying with air pollution regulations.

Since some of the plants in the sample are observed having negative short-run profits the intensity variables sum to one to allow for positive, negative, or zero maximal profits. This summing up condition can be altered to estimate the technology under non-increasing or constant returns to scale, something that is further discussed in the result section.

To identify compliance costs, the DEA model in equation 15 must be computed twice for each plant. In the first computation, the materials balance constraints from equation 3 are included in the model. Equation 15 then determines the maximal short run profits for the emission restricted technology. In the second computation the materials balance constraints are omitted, and the optimization problem defines the traditional (unrestricted) profit maxima. A similar approach is proposed by Färe et al. (2004), who assess the effect of risk-based capital requirements in banking on Nerlovian profit scores. Consider also calculating “hybrid models”, where a subset of the overall emissions constraints is applied in the estimations. These programs allow determining the relative importance of the different emission constraints with respect to regulatory compliance costs.

The directional distance function is also calculated for each plant. For plant *l′*, it is defined as:

$$
\vec{D}\left(x^{l'}, y^{l'}; -g_v, 0, g_y\right) = \max_{\beta,\lambda} \beta : \quad
\begin{aligned}
&\sum_{l=1}^{L} \lambda^l y_m^l \geq y_m^{l'} + \beta y_m^{l'} && m = 1,\ldots\ldots, M \\
&\sum_{l=1}^{L} \lambda^l x_n^l \leq x_n^{l'} - \beta\, x_n^{l'} && \mathrm{n} = 1,\ldots\ldots\ldots, V \\
&\sum_{l=1}^{L} \lambda^l x_n^l \leq x_n^{l'} && \mathrm{n{=}V{+}1,\ldots.,N} \\
&\lambda^l \geq 0, \quad l = 1,\ldots., L, && \sum_{l=1}^{L} \lambda^l = 1
\end{aligned}
\qquad (16)
$$

Applying the observed levels of variable inputs and desirable outputs as the direction vector, the profit differences in equations 13 and 14 are normalized by the sum of observed revenue and variable costs. It may be considered a proxy for the size of the plant (Färe et al., 2004).

3.2. DATASET - U.S. ELECTRICITY GENERATION

The Acid Rain Program was introduced in 1995 to reduce American power plants’ emissions of NO_X and SO_2. Additional programs, including the federal NO_X Budget Trading Program and the Clean Air Interstate Rule, were added later. Annual aggregate SO_2 emissions declined from 13,000 to 4,000 thousand metric tons, and annual NO_X emissions declined from 6,000 to 2,000 thousand metric tons in the period from 1995 to 2012. Recent declines in emissions may be influenced by the financial crises of 2007-2008 and not only by environmental legislation.

Fuel substitution has been an important measure for compliance with the Acid Rain regulations. This includes switching between different types of coal, or substituting coal with other fossil fuels. The latter includes switching to natural gas that emits substantially less NO_X and SO_2 per unit of fuel than coal. Recent years have seen great changes in the prices for fossil fuels, and over time natural gas has become a more economically viable alternative to coal. The average price for coal rose steadily from 120 cents/mmBTU in the year 2000 to 243 cents/mmBTU in 2012. The average price for natural gas, on the other hand, was highly fluctuating in the same period. It rose from 430 cents/mmBTU in the year 2000 to 830 cents/mmBTU in 2005, causing a major shift in the relative price between coal and gas in this period. The gas price remained high and volatile until it fell to 550 cents/mmBTU in 2009. It has been steadily declining since, largely as a result of the maturing of alternative technologies for natural gas extraction. In 2012, the average gas price was 370 cents/mmBTU, only 127 cents higher than the average coal price.

Coal-to-gas substitution is an interesting case study for empirical examination of regulatory induced allocative efficiencies because increasing (decreasing) gas prices are likely to raise (lower) the costs of regulatory compliance. When coal-to-gas switching becomes expensive, the designated producers are likely to choose other tools for compliance, e.g. pollution controls or purchases of emission allowances. If these options are unavailable or too costly the result may be an induced slowdown in the generation of electricity.

The model framework outlined in section 2 is applied to regulated American power plants with coal-to-gas substitution capacities. Following Welch and Barnum (2009), only plants that obtain at least one percent of their energy input from both coal and gas in year 2002 are included in the sample to model a homogeneous production technology. The average price for gas was low in 2002, implying that plants with coal-to-gas substitution capacities are likely to have exploited this opportunity that year. Plants that satisfy the selection criterion in 2002 and use both coal and gas as energy inputs in the following years are kept in the sample. Producers that convert to single fuel production after 2002 are excluded to avoid corner solutions. These selection criteria result in a sample of 67 power plants in operation from 2002 to 2008.

The DEA technology defined by equations 15 and 16 is assumed to consist of one desirable output, electricity, and two variable inputs, coal and gas. Coal and gas capacities are treated as quasifixed inputs and SO_2 and NO_x as bad outputs. The capacities approximate the capital inputs of the production stage. While previous studies (e.g., Hampf and Rødseth (2015a)) focus on aggregate capacity, I distinguish between coal and gas capacities as the plants' abilities to substitute among coal and gas clearly depend on their shares.

While similar studies on electricity generation (e.g. Färe et al. (2005; 2007)) frequently account for labor, some recent studies (e.g., Hampf and Rødseth (2015a) and Mekaroonreung and Johnson (2012)) advocate omitting labor because the limited availability of data contributes to a significant reduction in the (potential) sample size (see Hampf (2014) for an example). Labor is also considered a less important input when evaluating the environmental efficiencies of power plants; see Welch and Barnum (2009) for details. Moreover, labor is a non-polluting input. This means that its emission factor is zero, and that the consumption of labor is not restricted by environmental regulations. This paper emphasizes inputs whose consumption is indirectly constrained by environmental regulation.

The form EIA-906/920 provides monthly information on the plants' fuel consumption and net generation. This information is aggregated up to annual levels. Prices and sulfur contents of the fuels are obtained from EIA-423/923, while the overall generating capacities are obtained from EIA's statistics on capacity. They are further divided into coal capacities and gas capacities by applying information on each boiler's primary and secondary fuels. The sales prices for electricity are calculated from the power plants' retail and resale revenues, collected from EIA-861. Following Färe et al. (2005), the sales prices are taken to be the average of the retail and resale prices.

Emission factors are required to imbed the materials balance conditions in the model. For the case of air pollution from electricity generation, only the fossil fuels are considered pollution-generating inputs and the recuperation factors for the intended output are zero (i.e., there is no sulfur or nitrogen embodied in the electricity output). Appendix *A* of EIA's Electric Power Annual provides an overview of emission factors for various sub-groups of coal and gas that vary across different types of boilers. As our analysis is at the plant level, not at the boiler level, we construct plant-specific emission factors by applying fuel-specific emission factors given by the average of their boiler-specific counterparts[6]. When

[6] Boiler-specific emission factors were derived in Rødseth, K.L., Romstad, E., 2014. Environmental regulations, producer responses, and secondary benefits: carbon dioxide reductions under the Acid Rain Program Environ Resour Econ 59, 111-135., but only for some of the years under consideration in this paper. Comparing the Nerlovian efficiency scores for 2005 with the corresponding results using Rødseth and Romstad's data based on a set of non-parametric tests, I find that the simplifying assumption of an average-boiler emission factor has negligible impacts on the efficiency scores.

calculating SO_2-emissions, the emission factors are adjusted with the plant-specific average sulfur contents of the fuels as specified by EIA. Moreover, they are converted into tons of emissions per unit of weight of fuels. Uncontrolled emissions of NO_x and SO_2 are obtained by multiplying the derived emission factors with the plants' fuel inputs.

Aggregate variables for coal and gas rather than the fuels' subgroups are used as inputs. The purpose is to avoid missing observations for the disaggregated inputs and to emphasize coal-to-gas substitution rather than intrafuel-substitution. Aggregate emission factors for coal and gas are defined by the weighted sum of the emission factors for the fuels' sub-groups, using the share of fuels purchased from the various subgroups as weights to capture that different subgroups generate different amounts of air pollution. Summary statistics for the variables in the dataset are provided by table 3 in appendix A.

Figure 2 plots the ratio of average coal-to-gas quantities and corresponding relative prices, to highlight the sample's capacity to substitute between coal and gas. In 2002, the amount of gas used for electricity production is the highest observed due to its low price. In the following years, the sample's consumption of gas declines as the gas price doubles from 2002 to 2005, making coal-to-gas switching a less attractive instrument for regulatory compliance. Increasing prices for coal in the period following 2004 distort the price ratio and again provide the plants with incentives to increase their relative gas consumption.

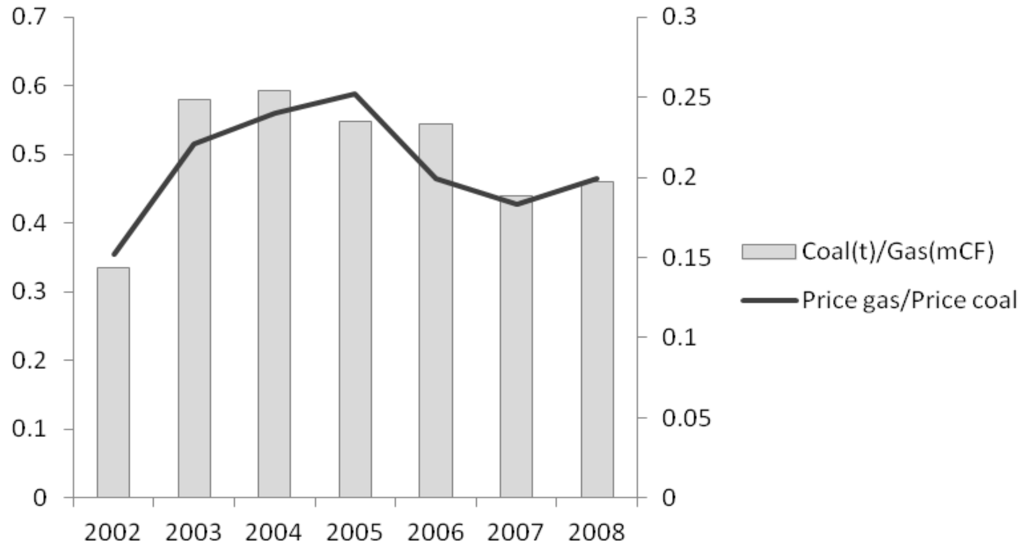

Figure 2: *Ratio of coal to gas quantities and prices for the plants in the sample*

4. RESULTS

The linear programming problems for maximal profits and the directional distance function are estimated for each plant in each year between 2002 and 2008. The emission restricted profit maximum is estimated three times to account for compliance costs related specifically to SO_2 or NO_x emissions; first with both the SO_2 and NO_x constraints included in the DEA model, second with the SO_2 constraint separately, and third with the NO_x constraint separately. In total, four programming problems for maximal profits – three emissions restricted and one unrestricted – are estimated for each plant in each year. All linear programming problems are solved under the assumption that the sum of the intensity variables, λ, is equal to one. This condition results in the inner approximation to the true technology, allowing for variable returns to scale (VRS). Alternatively, the DEA models can be estimated under non-increasing returns to scale (NIRS) or constant returns to scale (CRS).

A battery of nonparametric tests[7] - the Kolomogorov-Smirnov, ANOVA, Wilcoxon, and Median tests - reveal no differences (α=0.05) between the NIRS and VRS specifications in terms of Nerlovian, technical, and allocative efficiencies[8]. The ANOVA and Wilcoxon tests suggest that the "emission restricted" Nerlovian efficiency scores differ for the CRS and VRS specifications in four of the eight years considered due to differences in the estimates of technical efficiency. Since the allocative efficiency scores, *not* the technical efficiency scores, receive attention in this paper, the emphasis is solely on the VRS scores in the following. Table 1 provides an overview of mean Nerlovian efficiencies (NE), allocative efficiencies (AE), and technical efficiencies (TE). Standard deviations for the estimates are reported in brackets.

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[7] The printout from these tests is not reported due to space. The printouts are available from the author upon request.

[8] The only exception is the ANOVA test which suggests differences in technical efficiency scores for the years 2003, 2004, and 2007.

Table 1: *Mean Nerlovian (NE), allocative (AE), and technical (TE) efficiencies (St.dev)*

YEAR	2002	2003	2004	2005	2006	2007	2008
			Both emission constraints				
NE	0.190	0.234	0.212	0.238	0.240	0.217	0.224
	(0.196)	(0.224)	(0.215)	(0.223)	(0.302)	(0.216)	(0.297)
AE	0.100	0.093	0.082	0.090	0.107	0.095	0.119
	(0.109)	(0.107)	(0.113)	(0.105)	(0.206)	(0.141)	(0.221)
			SO_2 constraint				
NE	0.209	0.239	0.214	0.239	0.242	0.222	0.227
	(0.226)	(0.231)	(0.217)	(0.224)	(0.305)	(0.219)	(0.302)
AE	0.119	0.098	0.084	0.091	0.109	0.099	0.123
	(0.140)	(0.116)	(0.116)	(0.107)	(0.209)	(0.145)	(0.228)
			NO_x constraint				
NE	0.191	0.236	0.214	0.240	0.243	0.220	0.225
	(0.197)	(0.224)	(0.215)	(0.224)	(0.302)	(0.216)	(0.297)
AE	0.101	0.095	0.084	0.092	0.109	0.098	0.121
	(0.109)	(0.107)	(0.114)	(0.106)	(0.206)	(0.141)	(0.221)
			Without emission constraints				
NE	0.384	0.445	0.347	0.344	0.384	0.458	0.300
	(0.503)	(0.583)	(0.453)	(0.338)	(0.636)	(1.155)	(0.432)
AE	0.295	0.304	0.217	0.196	0.251	0.335	0.195
	(0.449)	(0.534)	(0.411)	(0.238)	(0.574)	(1.153)	(0.368)
			Techical efficiency				
TE	0.090	0.141	0.130	0.148	0.133	0.123	0.104
	(0.111)	(0.131)	(0.126)	(0.150)	(0.132)	(0.117)	(0.123)

Nerlovian efficiency averages between 0.19 and 0.24 for the model with both emission constraints. Its components – technical and allocative efficiencies – change little over time for this model specification. Mean allocative efficiencies range from 0.08 to 0.12, while mean technical efficiencies range from 0.09 to 0.15[9]. Their corresponding standard deviations are modest and change little over time.

[9] The choice of observed variable inputs and outputs as the direction vector for the directional distance function provides a natural interpretation for the TE estimates: When multiplied with 100 they report the percentage change in a plant's variable inputs and outputs that would put the plant on the boundary of the estimated reference technology.

When the DEA model is estimated with either the SO_2 constraint separately or the NO_X constraint separately, the efficiency scores rise only slightly[10]. When, on the other hand, both emission constraints are omitted, the allocative efficiency scores increase substantially. Mean Nerlovian efficiencies then range between 0.30 and 0.46, while mean allocative efficiencies range between 0.20 and 0.34 for the model estimated without emission constraints.

The difference between the allocative efficiency scores estimated with and without the emission constraints is a normalized measure of forgone profits due to environmental regulations. It fluctuates over time and ranges from 0.08 to 0.24 for the model estimated with both emission constraints. The corresponding standard deviations are also large and fluctuating, indicating that the plants in the sample are affected asymmetrically by the current regulations.

Nonparametric testing of differences in the allocative efficiency scores estimated with and without the emission constraints is undertaken to evaluate whether the existing environmental regulations significantly affect the profitability of power generation. The null hypothesis for all tests is that there are no differences between the efficiency scores estimated with and without emission constraints in terms of their mean and distribution. Table 2 reports the test statistics for the Kolomogorov-Smirnov (KSM), ANOVA, Wilcoxon (WILC), and Median (MEDI) tests. P-values are reported in brackets.

[10] A battery of statistical tests suggests that there are no differences between the allocative efficiency scores calculated with the SO_2 and NO_x constraints separately.

Table 2: *Tests for differences in allocative efficiencies. Test statistics (P-values)*

YEAR	2002	2003	2004	2005	2006	2007	2008
KSM	0.269	0.299	0.284	0.269	0.239	0.239	0.134
	(0.010)	(0.003)	(0.005)	(0.010)	(0.029)	(0.029)	(0.507)
ANOVA	11.860	10.010	6.690	11.110	3.740	2.880	2.100
	(0.001)	(0.002)	(0.011)	(0.001)	(0.055)	(0.092)	(0.150)
WILC	3.018	2.976	2.793	2.337	1.890	2.374	1.440
	(0.003)	(0.003)	(0.005)	(0.019)	(0.059)	(0.018)	(0.150)
MEDI	6.716	5.045	8.627	3.612	0.746	2.418	0.746
	(0.010)	(0.025)	(0.003)	(0.057)	(0.388)	(0.120)	(0.388)

*Tests for differences in allocative efficiency scores calculated with and without emission constraints for SO_2 and NO_x

The test results indicate that the regulatory constraints for SO_2 and NO_x have significant impact on profitability. Mixed results are obtained for the years 2006 and 2007, where in 2006 the Kolomogorov-Smirnov test is the only test that rejects the null hypothesis at the 5 percent level, and in 2007 both the Kolomogorov-Smirnov and Wilcoxon tests reject the null hypothesis while the ANOVA and Median tests do not. All four tests are unable to reject the null hypothesis in 2008. This result is an example of how market conditions influence the costs of complying with environmental regulations. That is, the outbreak of the financial crisis of 2007-2008 is likely to have reduced the profitability of electricity generation and thereby also lowered the power plants' compliance costs.

Overall, the results suggest that regulatory implications for allocative efficiency should receive more attention in future research. Tables 1 and 2 support the proposition that overall efficiency evaluations will underestimate environmentally regulated producers' allocative efficiencies if the economic analysis ignores environmental constraints that influence their production possibilities. The allocative efficiency scores increase on average by 0.16 when the emission constraints are omitted, and the differences between the allocative efficiency scores estimated with and without emission constraints are found to be statistically significant for most years between 2002 and 2008.

In a recent paper, Aparicio et al. (2013) argue that the Nerlovian profit efficiency measure has no obvious economic interpretation. They propose a modified directional distance function that allows outputs to expand and inputs to contract by different proportions, and show that their distance function is dual to a Nerlovian-type profit measure where costs instead of the sum of costs and revenues make up the denominator of the profit efficiency measure. As a sensitivity test, I calculate the Aparicio et al.'s modified Nerlovian profit measure and directional distance function. The results are reported in appendix B. While the magnitudes of the efficiency scores generally are larger for Aparicio et al.'s approach than for the traditional Nerlovian efficiency approach, both approaches result on average in far larger allocative efficiency scores when emission constraints are ignored. Moreover, the intertemporal developments of the efficiency scores appear aligned. Using Aparicio et al.'s approach, the majority of the non-parametric tests indicate significant differences between allocative efficiency scores calculated with and without emission constraints from 2002 to 2004. In the following years, only the Anova test indicates significant differences between these efficiency scores. In 2008, none of the tests suggest statistic differences between the efficiency scores.

According to equation 4, the plants' production plans are expected to be set according to the rule that their marginal costs of cleaning up emissions or purchasing emission permits equal the marginal economic benefits from being able to increase their emissions; cf. figure 1. Changes in profits which follow by a marginal relaxation of the emission constraints thereby reflect the plants' marginal abatement costs.

Marginal abatement cost estimates are obtainable from the dual of the DEA program in equation 15, by evaluating the shadow prices (or dual variables) on the SO_2 and NO_x

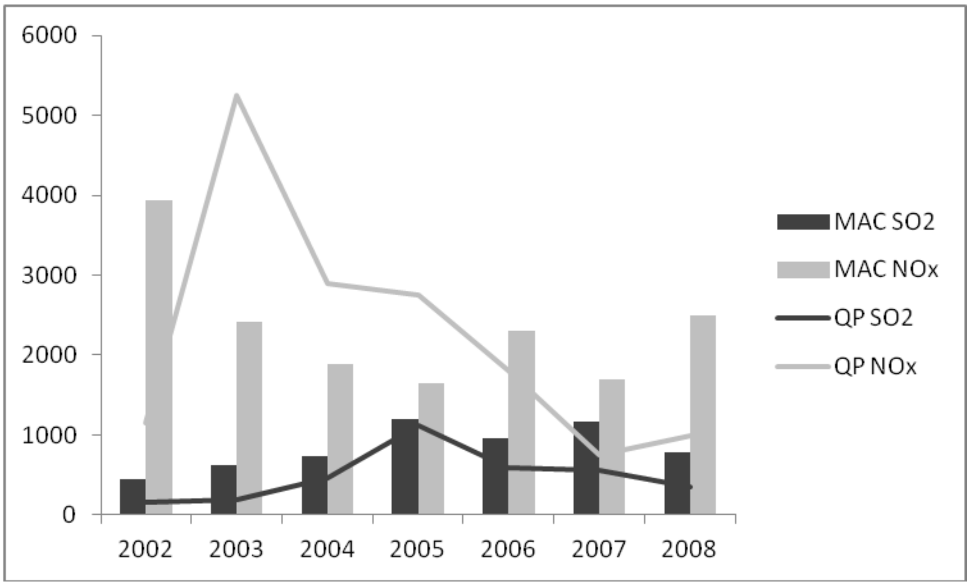
constraints. However, since multiple solutions to the dual problem may exist the shadow prices are not necessarily unique; see Rosen et al. (1998) for more details. The solution to equation 15 is, on the other hand, unique. One option is to approximate the shadow price by manually calculating the maximal profits that result by one unit (i.e., one ton) relaxation of the SO_2 and NO_x constraints, respectively. Formally[11]:

$$
\begin{aligned}
MAC_{SO_2} &= \pi^C\left(r, w, x_f, b_{SO_2} + a_{SO_2} + 1, b_{NO_x} + a_{NO_x}\right) - \pi^C\left(r, w, x_f, b + a\right) \\
MAC_{NO_2} &= \pi^C\left(r, w, x_f, b_{SO_2} + a_{SO_2}, b_{NO_x} + a_{NO_x} + 1\right) - \pi^C\left(r, w, x_f, b + a\right)
\end{aligned}
\qquad (17)
$$

Figure 3 reports the mean marginal abatement cost estimates for SO_2 (the black bars) and NO_x (the grey bars) and the corresponding mean quota prices for SO_2 (the black line) and NO_x (the grey line).

The marginal abatement cost estimates are of the same magnitudes as the quota prices, in particular for SO_2. This is not surprising since the Acid Rain Program includes market-based regulation for SO_2, while the regulations for NO_x are to a larger extent based on emission standards. Given a well-functioning quota market for SO_2, the quota price will reflect the units' marginal abatement costs.

[11] Note that equation 17 can be perceived as defining the partial directional derivative "to the right" of the current emission constraint. See Rosen et al. (1998, p. 213) for more details.



*The quota prices are set equal to averages of the price intervals reported by Mekaroonreung and Johnson (2012)

Figure 3: *Marginal abatement costs and quota prices (Dollar per ton)*

The marginal abatement cost estimates for NO_x are in general higher than for SO_2, which is in line with the reported quota prices. The estimates' temporal pattern follows the the quota prices; cf. the decline in the average marginal abatement cost for NO_x and the increase in the average marginal abatement cost for SO_2 in the period between 2002 and 2005. This contrasts the results of Mekaroonreung and Johnson's (2012) recent comprehensive study on shadow prices of U.S. power plants' SO_2 and NO_x emissions. Their (best) results suggest that the average marginal abatement cost for SO_2 was 262 dollar per ton, and that it was relatively stable in the period between 2002 and 2008. The steep increase in the quota price for SO_2 between 2002 and 2005 is thus not reflected by their estimates. Mekaroonreung and Johnson further found an average marginal abatement cost of 912 dollar per ton of NO_x. While the magnitudes of their NO_x shadow prices are reasonable, their estimates suggest that the marginal abatement costs for NO_x peeked in

2005. This is the opposite of the developments of the corresponding quota price and the results obtained in this study.

In the period from 2006 to 2008, the marginal abatement cost estimates are on average higher than the quota prices, both for SO_2 and NO_x. This may be the result of the Clean Air Interstate Rule (CAIR) that was issued by the Environmental Protection Agency in 2005. This program was more ambitious than the Clean Air regulations and is likely to have increased the power producers' compliance costs.

5. SUMMARY AND CONCLUSIONS

This paper examines the proposition that failing to control for the implications of environmental regulations on the performances of regulated decision making units results in biased efficiency measurement. A modeling approach that allows disentangling managerial and regulatory induced allocative inefficiencies is proposed. Regulatory induced allocative inefficiencies are representations of the producers' compliance costs and consequentially provide important economic insights to policy makers.

The paper utilizes DEA to compute the Nerlovian profit efficiencies and their technical and allocative efficiency components for a sample of 67 U.S. power plants equipped with coal-to gas substitution capabilities. The sample is observed in the period from 2002-2008, a period with fluctuating fuel prices and increasingly more stringent environmental regulations. The empirical results support the proposal that failing to control for the impact of environmental regulations leads to biased efficiency measurement as the allocative efficiency scores are about 2.7 times larger when existing environmental regulations are not accounted for. The modeling approach also proves useful for deriving marginal abatement cost estimates that not only are of the same magnitudes as the quota prices for SO_2 and NO_x, but also largely follow their fluctuations.

Several previous contributions to environmental economics have been concerned with the implications of environmental regulations for technical efficiency. The empirical results of this paper suggest that this discussion should be broadened to also include allocative efficiency. Future research should focus on developing methods and approaches that allow joint evaluation of the implications of environmental regulations on technical and allocative efficiencies, and to develop new knowledge about how different compliance strategies affect the two types of efficiencies. New insights on these issues will facilitate a better understanding of the economic implications of environmental regulations.

6. REFERENCES

Aparicio, J., Pastor, J.T., Ray, S.C., 2013. An overall measure of technical inefficiency at the firm and at the industry level: The 'lost profit on outlay'. Eur J Oper Res 226, 154-162.

Ayres, R.U., Kneese, A.V., 1969. Production, consumption, and externalities. Amer Econ Rev 59, 282-297.

Ball, E., Färe, R., Grosskopf, S., Zaim, O., 2005. Accounting for externalities in the measurement of productivity growth: the Malmquist cost productivity measure. Struct Change Econ Dynam 16, 374-394.

Brännlund, R., Chung, Y.H., Färe, R., Grosskopf, S., 1998. Emissions trading and profitability: The Swedish pulp and paper industry. Environ Resour Econ 12, 345-356.

Brännlund, R., Färe, R., Grosskopf, S., 1995. Environmental regulation and profitability: an application to Swedish pulp and paper mills. Environ Resour Econ 6, 23-36.

Chambers, R.G., 1988. Applied production analysis: a dual approach. Cambridge University Press, Cambridge.

Chambers, R.G., Chung, Y.H., Färe, R., 1998. Profit, directional distance functions, and Nerlovian efficiency. J Optimiz. Theory App. 98, 351-364.

Chung, Y.H., Färe, R., Grosskopf, S., 1997. Productivity and undesirable outputs: a directional distance function approach. J Environ Manage 51, 229-240.

Coelli, T., Lauwers, L., Van Huylenbroeck, G., 2007. Environmental efficiency measurement and the materials balance condition. J Productiv Anal 28, 3-12.

Ebert, U., Welsch, H., 2007. Environmental emissions and production economics: implications of the materials balance. Am J Agr Econ 89, 287-293.

Frisch, R., 1965. Theory of production. Reidel, Dordrecht.

Färe, R., Grosskopf, S., Lee, H., 1990. A nonparametric approach to expenditure-constrained profit maximization. Am J Agr Econ 72, 574-581.

Färe, R., Grosskopf, S., Lovell, C.A.K., Pasurka, C.A., 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. Rev Econ Stat 71, 90-98.

Färe, R., Grosskopf, S., Noh, D.-W., Weber, W.L., 2005. Characteristics of a polluting technology: theory and practice. J Econometrics 126, 469-492.

Färe, R., Grosskopf, S., Pasurka, C.A., 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. J Regional Sci 41, 381-409.

Färe, R., Grosskopf, S., Pasurka, C.A., 2007. Pollution abatement activities and traditional productivity. Ecolog Econ 62, 673-682.

Färe, R., Grosskopf, S., Pasurka, C.A., 2013a. Joint production of good and bad outputs with a network application, in: Shogren, J.F. (Ed.), Encyclopedia of Energy, Natural Resources and Environmental Economics. Elsevier, San Diego.

Färe, R., Grosskopf, S., Pasurka, J.C.A., 2013b. Tradable permits and unrealized gains from trade. Energ Econ 40, 416-424.

Färe, R., Grosskopf, S., Pasurka Jr, C.A., 2014. Potential gains from trading bad outputs: The case of U.S. electric power plants. Resour Energy Econ 36, 99-112.

Färe, R., Grosskopf, S., Weber, W.L., 2004. The effect of risk-based capital requirements on profit efficiency in banking. Appl Econ 36, 1731-1743.

Färe, R., Logan, J., 1983. The rate-of-return regulated firm: cost and production duality. Bell Journal of Economics 14, 405-414.

Førsund, F.R., 2009. Good modelling of bad outputs: pollution and multiple-output production. Int Rev Environ Resour Econ 3, 1-38.

Førsund, F.R., Strøm, S., 1988. Environmental economics and management: pollution and natural resources. Croom Helm, London.

Granderson, G., Prior, D., 2013. Environmental externalities and regulation constrained cost productivity growth in the US electric utility industry. J Productiv Anal 39, 243-257.

Hampf, B., 2014. Separating environmental efficiency into production and abatement efficiency - a nonparametric model with application to U.S. power plants. J Productiv Anal 41, 457-473.

Hampf, B., Rødseth, K.L., 2015a. Cabon dioxide standards for U.S. power plants: An efficiency analysis perspective. Energ Econ 50, 140-153.

Hampf, B., Rødseth, K.L., 2015b. Optimal profits under environmental regulation: the benefits from emission intensity averaging. Annals of Operations Research, 1-24.

Jaffe, A.B., Peterson, S.R., Portney, P.R., Stavins, R.N., 1995. Environmental regulation and the competitiveness of U.S. manufacturing: what does the evidence tell us? J Econ Lit 33, 132-163.

Krysiak, F.C., Krysiak, D., 2003. Production, consumption, and general equilibrium with physical constraints. J Environ Econ Manage 46, 513-538.

Lauwers, L., 2009. Justifying the incorporation of the materials balance principle into frontier-based eco-efficiency models. Ecolog Econ 68, 1605-1614.

Lee, H., Chambers, R.G., 1986. Expenditure constraints and profit maximization in U.S. agriculture. Am J Agr Econ 68, 857-865.

Mekaroonreung, M., Johnson, A.L., 2012. Estimating the shadow prices of SO2 and NOx for U.S. coal power plants: A convex nonparametric least squares approach. Energ Econ 34, 723-732.

Murty, S., Russell, R.R., Levkoff, S.B., 2012. On modeling pollution-generating technologies. J Environ Econ Manage 64, 117-135.

Oude Lansink, A., Van Der Vlist, A., 2008. Non-parametric modelling of CO2 emission quota. Journal of Agricultural Economics 59, 487-497.

Palmer, K., Oates, W.E., Portney, P.R., 1995. Tightening environmental standards: the benefit-cost or the no-cost paradigm? J Econ Perspect 9, 119-132.

Pethig, R., 2003. The "materials balance" approach to pollution: its origin, implications and acceptance, Economics Discussion Paper. University of Siegen.

Pethig, R., 2006. Non-linear production, abatement, pollution and materials balance reconsidered. J Environ Econ Manage 51, 185-204.

Porter, M., Van Der Linde, C., 1995. Toward a new conception of the environment-competitiveness relationship. J Econ Perspect 9, 97-118.

Rosen, D., Schaffnit, C., Paradi, J.C., 1998. Marginal rates and two-dimensional level curves in DEA. J Productiv Anal 9, 205-232.

Rødseth, K.L., 2013. Capturing the least costly way of reducing pollution: a shadow price approach. Ecolog Econ 92, 16-24.

Rødseth, K.L., 2014. Efficiency measurement when producers control pollutants: a non-parametric approach. J Productiv Anal 42, 211-223.

Rødseth, K.L., 2015. Axioms of a polluting technology: A materials balance approach. Environ Resour Econ.

Rødseth, K.L., Romstad, E., 2014. Environmental regulations, producer responses, and secondary benefits: carbon dioxide reductions under the Acid Rain Program Environ Resour Econ 59, 111-135.

Shadbegian, R.J., Gray, W.B., 2005. Pollution abatement expenditures and plant-level productivity: A production function approach. Ecolog Econ 54, 196-208.

Shephard, R.W., 1974. Indirect production functions. Anton Hain, Meisenhaven am Glan.

Welch, E., Barnum, D., 2009. Joint environmental and cost efficiency analysis of electricity generation. Ecolog Econ 68, 2336-2343.

7. APPENDIX A

Table 3: *Summary Statistics*

		YEAR						
		2002	2003	2004	2005	2006	2007	2008
$COAL$	(t)	1207965.0	1184212.0	1272225.0	1282352.0	1292302.0	1285967.0	1243757.0
		(1219278.0)	(1225455.0)	(1257144.0)	(1287343.0)	(1294303.0)	(1226576.0)	(1239058.0)
GAS	(mCF)	3609969.0	2045929.0	2143212.0	2342252.0	2371563.0	2928845.0	2700399.0
		(7113197.0)	(4443897.0)	(4817720.0)	(5286427.0)	(4996507.0)	(5701523.0)	(6226449.0)
EL	(MwH)	2840733.0	2643367.0	2813297.0	2836137.0	2817207.0	2880542.0	2735781.0
		(2997614.0)	(2807723.0)	(2814453.0)	(2895691.0)	(2898768.0)	(2906832.0)	(2855661)
$COAL$ CAP	(MW)	364.2	364.2	351.5	350.9	350.6	360.5	379.7
		(377.1)	(377.1)	(365.4)	(365.7)	(365.4)	(393.0)	(408.2)
GAS CAP	(MW)	327.6	327.6	355.9	356.6	366.5	363.3	355.0
		(331.8)	(331.8)	(347.7)	(347.9)	(361.6)	(338.1)	(336.6)
$b_{SO_2}^{UC}$	(t)	15368.8	14446.7	15797.5	16849.9	17171.0	16684.6	16236.3
		(19200.0)	(18264.6)	(18645.7)	(21840.7)	(22536.4)	(22033.1)	(22208.4)
$b_{NO_X}^{UC}$	(t)	7054.9	6669.1	7181.8	7377.1	7445.7	7530.2	7204.0
		(7089.2)	(7039.0)	(6989.6)	(7350.7)	(7394.0)	(7317.3)	(7086.3)
$n_{SO_2}^{COAL}$		$1.51e^{-02}$	$1.48e^{-02}$	$1.51e^{-02}$	$1.59e^{-02}$	$1.56e^{-02}$	$1.48e^{-02}$	$1.56e^{-02}$
		$(1.28e^{-02})$	$(1.25e^{-02})$	$(1.27e^{-02})$	$(1.44e^{-02})$	$(1.31e^{-02})$	$(1.22e^{-02})$	$(1.40e^{-02})$
$n_{NO_X}^{COAL}$		$5.70e^{-03}$	$5.68e^{-03}$	$5.73e^{-03}$	$5.77e^{-03}$	$5.76e^{-03}$	$5.76e^{-03}$	$5.75e^{-03}$
		$(1.25e^{-03})$	$(1.38e^{-03})$	$(1.24e^{-03})$	$(1.22e^{-03})$	$(1.23e^{-03})$	$(1.23e^{-03})$	$(1.23e^{-03})$
$n_{SO_2}^{GAS}$		$3.00e^{-07}$	$3.00e^{-07}$	$3.00e^{-07}$	$3.00e^{-07}$	$3.00e^{-07}$	$3.00e^{-07}$	$3.00e^{-07}$
		$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$
$n_{NO_X}^{GAS}$		$1.40e^{-04}$	$1.40e^{-04}$	$1.40e^{-04}$	$1.40e^{-04}$	$1.40e^{-04}$	$1.40e^{-04}$	$1.40e^{-04}$
		$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$	$(0.00e^{+00})$
r_{EL}		45.7	47.3	48.2	57.4	60.7	61.6	66.8
		(9.8)	(10.7)	(11.1)	(15.4)	(16.6)	(13.2)	(15.8)
w_{COAL}		28.1	27.8	30.2	36.6	40.1	42.9	50.3
		(10.5)	(9.9)	(12.8)	(16.6)	(17.6)	(18.5)	(24.2)
w_{GAS}		4.3	6.1	7.3	9.2	8.0	7.9	10.0
		(1.4)	(1.2)	(2.9)	(1.3)	(0.9)	(1.1)	(2.4)

8. APPENDIX B

Table 4: *Mean Nerlovian (NE), allocative (AE), and technical (TE) efficiencies (St.dev)*

YEAR	2002	2003	2004	2005	2006	2007	2008
			Both emission constraints				
NE	0.690	0.887	0.777	0.847	0.838	0.634	0.690
	(0.678)	(0.878)	(0.757)	(0.791)	(1.131)	(0.660)	(0.912)
AE	0.513	0.605	0.504	0.511	0.540	0.355	0.429
	(0.507)	(0.656)	(0.542)	(0.537)	(0.918)	(0.466)	(0.671)
			Without emission constraints				
NE	1.347	1.575	1.227	1.214	1.331	1.037	0.936
	(1.634)	(1.875)	(1.480)	(1.260)	(2.334)	(1.547)	(1.324)
AE	1.171	1.294	0.954	0.877	1.034	0.757	0.675
	(1.525)	(1.743)	(1.370)	(1.039)	(2.180)	(1.477)	(1.129)
			Techical efficiency				
TE	0.177	0.281	0.270	0.336	0.297	0.280	0.261
	(0.219)	(0.264)	(0.276)	(0.371)	(0.327)	(0.292)	(0.353)

Table 5: *Tests for differences in allocative efficiencies. Test statistics (P-values)*

YEAR	2002	2003	2004	2005	2006	2007	2008
KSM	0.284	0.224	0.179	0.179	0.179	0.194	0.149
	(0.009)	(0.070)	(0.233)	(0.233)	(0.233)	(0.160)	(0.444)
ANOVA	11.220	9.010	6.160	6.580	2.880	4.460	2.320
	(0.001)	(0.003)	(0.014)	(0.011)	(0.092)	(0.037)	(0.130)
WILC	2.670	2.422	1.935	1.748	1.372	1.646	1.101
	(0.008)	(0.015)	(0.053)	(0.081)	(0.170)	(0.100)	(0.271)
MEDI	3.612	6.717	2.418	1.463	0.269	1.463	0.269
	(0.042)	(0.008)	(0.083)	(0.150)	(0.365)	(0.150)	(0.365)