Efficiency Trends in U.S. Coal-fired Energy Production & the 1990 Clean Air Act Amendment: A Nonparametric Approach

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DRAFT - December 2013; Original - August 2013

Abstract

This study examines the trends in efficiency in the electrical generation industry by examining the activities of 92 coal-fired electric plants during the 1985-1995 period across the United States. Extending Murty et. al. [2012], the joint production of electricity, NO_x, and SO_2 emissions are modeled under the assumption of residual *byproduction*. Technologies are estimated using data envelopment methods (DEA) and pollutant-level decomposable efficiency scores are jointly estimated for 1) expansions in electrical generation, 2) reductions in NO_x emissions, and 3) reductions in SO_2 emissions. The 1990 announcement of the Clean Air Act's Phase I SO_2 reductions was closely followed by a steady increase in efficiency in SO_2 reductions despite the regulation not requiring strict compliance until 1995, at which point there was a sharp drop in efficiency in electrical generation. Moreover, the firms forced to comply with Phase I SO_2 reductions, on average, suffered the greatest efficiency losses in electrical generation relative to unregulated firms.

1 Introduction

Recently, there has been much progress in the literature on modeling the joint production activities of pollution-generating technologies for applications in productivity analysis, growth, and more. Many of the nonconventional approaches to modeling pollution generation have converged on a general problem: how to accurately capture the trade offs implied by the joint production of residuals while preserving the physical constraints implied by the conservation of mass-energy from the laws of thermodynamics. Ayres and Kneese [1969] are credited for first pointing out that this need be taken into account when modeling accurately, the physical generation of residuals in the production process. More recently Coelli et al. [2007], Lauwers [2009], Pethig [2006], Forsund [2009], and Murty et. al. [2012] purport models of joint production in an attempt to improve the consistency with physical trade offs. The common trend amongst these papers is motivated by the desire to correct a fundamental flaw in standard treatments, which imply unrealistic trade offs between pollutants and intended production via a violation of the materials balance condition[1] and, as a result, may provide incorrect information regarding the actual costs producers face when emissions regulations become binding. The common solution to this problem generally relies on using separate implicit production relations to distinguish the independent generation of byproducts from the process that generates intended outputs. Murty, et. al. [2012] applies this tactic by utilizing two production relations: one to capture the intended production activities of electrical generation and another that captures the generation of pollutants, NO_x and SO_2, which are assumed to satisfy a *costly disposability* condition[2].

The difficulty in applying Murty, et al.'s [2012] byproduction modeling tactic, as will be made apparent momentarily, is that the modeler requires extensive information about the technology to be able to accurately partition the set of inputs that are associated with residual generation from those that are not[3]. Moreover, by still only utilizing one production relation to capture the joint production of two pollutants, the resulting reduced-form model implies, along the weakly efficient frontier, a rich

[1]The materials balance principle is an accounting identity implied by the conservation of mass energy accounting for residuals in production as the mass differential between the inputs and outputs. See Coelli et. al. [2007] for a formal definition. See Murty, et al. [2012] for a formal discussion of why standard treatments violate this condition.

[2]First formalized by Murty [2010].

[3]Conventional advise is to err on the side of caution and to include inputs when unsure and the DEA will not pick up the relation if it is not strong in the data. Otherwise, omission could be costly in misspecification

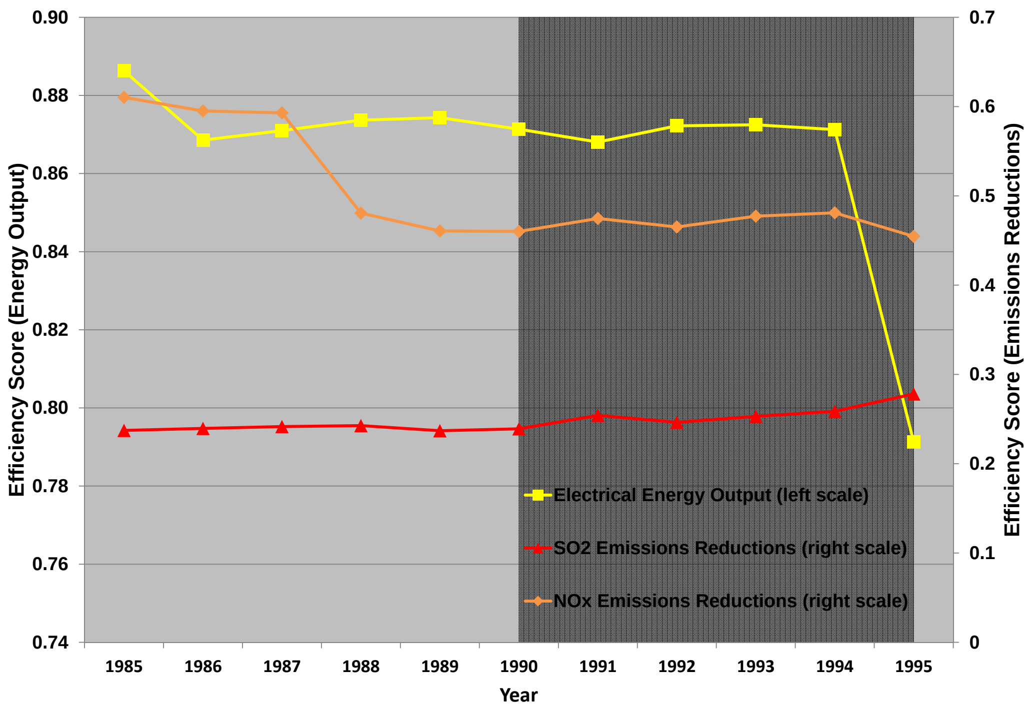
menu of NO_x and SO_2 vectors so that pollutants are substitutable for one another for a fixed input vector - inconsistent with materials balance. This study extends the model of Murty et. al. [2012] to correct a flaw in implied trade off between pollutants by modeling the byproduction technology as the intersection of not two, but three technology sets: one governing the independent production of electrical generation, and two others governing the independent residual generation of pollutants. The best practice frontiers implied by each of these independent relations are estimated via data envelopment (DEA) and efficiencies in production are constructed by implementing a metric that measures the distance an observed production vector lies from its projection to the estimated best practice frontier.

A consequence of this extension conveniently allows for the joint estimation of decomposable efficiency scores at the *pollutant* level, which Murty et. al. [2012] are unable to measure[4]. That is, the extended byproduction model allows for the decomposition of efficiency into three components: efficiency in electrical generation, efficiency in reduction of NO_x, and efficiency in reductions of SO_2. Finally, this study applies the extended modeling philosophy to estimate jointly, the variations in technical efficiency in electrical generation and the variations in efficiencies in emission reductions using a data set from 1985-1995 on the activities of 92 coal-fired electrical plants across the United States during a period when there was an important policy change: the Acid Rain Ruling (ARR), established under Title IV of the 1990 Clean Air

[4]They can only measure overall inefficiency in pollution reduction in the entire space of pollutants

Act Amendment (CAAA), mandated reductions in SO_2 and NO_x emissions requiring future compliance with a grace period to adjust before compliance becomes binding. Phase I of the ARR emissions reductions require reductions in SO_2 by the end of the 1990-1995 period.

Figure 0: Efficiency Trends
Energy Production & Emissions Reductions



In figure 0 above, the time series of efficiency scores show that at the end of the 11 year period, there was an abrupt decline in the output efficiency of electrical generating firms during the 1995 year when compliance with mandated SO_2 reductions became binding. The shaded region corresponds to years following the 1990 policy change. Throughout the sample period, efficiency in reductions of SO_2 steadily increased, and most rapidly subsequent to the 1990 policy announcement. Oddly, these increases in efficiency in SO_2 reductions are accompanied by a contemporaneous gradual decline in the efficiency in reducing NO_x emissions. After partitioning firms into two groups - those facing binding regulation and those that are unregulated, this study finds that firms facing binding mandates typically showed the greatest increases in efficiency in pollution reduction while at the same time suffering the greatest losses in the output efficiency of electrical generation.

2 Some Notation and Relevant Literature

Throughout the remainder of the paper, input vectors are denoted by $x \in \mathbf{R}_+^I$, intended output vectors by $y \in \mathbf{R}_+^J$, and unintended output (byproducts) vectors by $z \in \mathbf{R}_+^K$. Standard treatments of these types of technologies usually rely on a single implicit production relation that treat residual byproducts as either a standard freely disposable input[5] or as weakly disposable[6], null-joint[7] output[8]. The standard technology set is given by

$$T = \{\langle x, y, z\rangle \in \mathbf{R}_+^{I+J+K} | f(x, y, z) \leq 0\},$$

where f is differentiable and vectors satisfying $f(x, y, z) = 0$ are (weakly efficient) points on the boundary of the technology set. Any vectors satisfying $f(x, y, z) < 0$ are inefficient production vectors.

The literature on decomposing efficiency and factors associated with changes in pollution emissions has been extensive. Many of these studies have carried out analyses related to carbon emissions variations using either index decomposition (ID) mod-

[5]See Baumol and Oates [1975], Cropper and Oates [1992], Pittman [1981], and Barbera and McConnell [1990].

[6]First formalized by Shephard [1953]. A technology satisfies weak disposability of outputs if

$$\langle x, y, z\rangle \in T \implies \langle x, \lambda y, \lambda z\rangle \in T \quad \forall \quad \lambda \in [0, 1].$$

This implies that while pollution is not freely disposable, it is possible to reduce, in tandem, pollution and intended outputs.

[7]Null-jointness is satisfied if

$$\langle x, y, z\rangle \in T \wedge z = 0 \implies y = 0.$$

This condition implies that any positive level of intended production always generates some residual by-product.

[8]See Pittman [1983], Fare, Grosskopf, Lovell, and Pasurka[1989], Pasurka[2006], and Fare, Grosskopf, and Pasurka [1986] for an example of studies that assume weakly disposable, null-joint production.

els[9] similar to the one herein or structural decomposition analysis (SDA) models,[10] which utilize input-output tables.[11] While carbon emissions are of great importance in the environmental literature, this study focuses specifically on NO_x and SO_2 emissions. NO_x and SO_2 emissions are now subject to federal cap and trade policy under the Acid Rain Ruling, which was established under Title IV of the 1990 Clean Air Act Amendment to reduce acid deposition in the environment. Unlike studies analyzing only carbon emissions, where the production frontier consists of a single combination of good and bad output production for a given technology and input/intended output combination due to the absence of abatement activities, when NO_x and SO_2 emissions are generated, abatement options allow for multiple combinations of good and bad outputs to be produced for a given technology and input vector. Reducing carbon emission resulting from the burning of fossil fuels, on the other hand, requires either substitution between types of less emission intense fuels or substitution of non-fuel inputs for fuel inputs. Aiken and Pasurka [2002] specify a joint production model and attempt to quantify variations in SO_2 emissions associated with changes in technical efficiency, the output mix, and production levels in the United States manufacturing sector during the 80's and 90's. Pasurka [2003] extends this analysis by calculating the change in SO_2 emissions associated with the lack of free disposability of pollutants.

[9] See Lin and Chang [1996], Selden et al. [1999], Viguier [1999], Hammer and Lofgren [2001], Bruvoll and Medin [2003], and Cherp et al. [2003].

[10] See Leontief and Ford [1972], Meyer and Stahmer [1989], Wier [1998], Wier and Hasler [1999].

[11] For a comparison of these models, see Hoekstra and van der Bergh [2003]

3 The Byproduction Model and the Generalized Extension

The first part of this section introduces the byproduction model put forth in Murty et. al. [2012] and discusses the implications of this model. The latter portion of the section describes the generalized extension of the byproduction model.

3.1 The Byproduction Model

Partition the input vector $x = \langle x_{-\imath}, x_{\imath} \rangle$ where $x_{-\imath}$ is the input vector purged of the first $I' \leq I$ inputs that are associated with the pollutants z and let $x_{\imath}$ denote the subset of the input vector that are associated with the residual generation of pollutants.[12] Murty, et. al. [2012] specify the byproduction technology as:

$$T_{BP} = T_1 \cap T_2,$$

where

$$T_1 = \left\{ \langle x_{-\imath}, x_{\imath}, y, z \rangle \in \mathbf{R}_+^{I+J+K} \;\middle|\; f(x_{-\imath}, x_{\imath}, y) \leq 0 \; \right\},$$

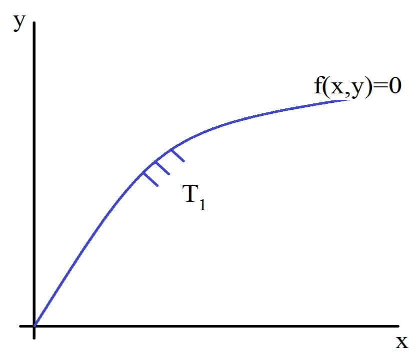
$$T_2 = \left\{ \langle x_{-\imath}, x_{\imath}, y, z \rangle \in \mathbf{R}_+^{I+J+K} \;\middle|\; g(z, x_{\imath}) \geq 0 \right\},$$

[12] In general, we need not restrict ourselves to the case where only input usage causes pollution. For example, the production of cheese causes an unintended odor from the presence of the output, not necessarily from input usage. See Murty, et. al. [2012] for a discussion of altering the model to accommodate for this type of situation.

and f and g are continuously differentiable functions.[13] T_1 is the standard technology set specifying the ways in which inputs are transformed into intended outputs. It is assumed that T_1 satisfies the standard free disposability conditions with respect to intended outputs and input usage:

$$\langle x, y, z\rangle \in T_1 \wedge \bar{x} \geq x \implies \langle \bar{x}, y, z\rangle \in T_1,$$

$$\langle x, y, z\rangle \in T_1 \wedge \bar{y} \leq y \implies \langle x, \bar{y}, z\rangle \in T_1.$$

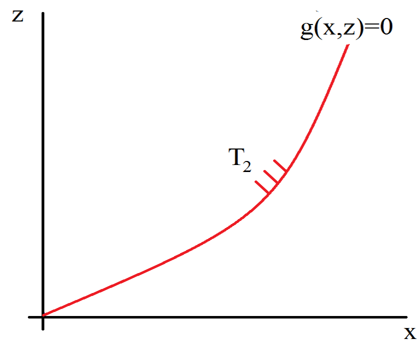


The differential restrictions on f imply

$$f_x(x, y) \leq 0 \quad \forall \quad i = 1 \ldots I$$

$$f_y(x, y) \geq 0 \quad \forall \quad j = 1 \ldots J.$$

[13] We assume that T_{BP} is non-empty. In fact, as long as a production vector in T_1 is feasible given the same component of pollution generating input causes some amount of pollution through T_2, then the intersection will be non-empty. If the no free lunch assumption holds, then the zero vector lies in both T_1 and T_2, so that T_{BP} is non-empty.



T_2 is nature's residual-generation set reflecting the physical and chemical mechanism underlying the production of pollutants. In the case of technologies generating pollutants, one can observe a certain minimal amount of z for a given $\langle y, x\rangle$ bundle. Inefficiencies arising in the production process through nature's residual generation mechanism can lead to excess generation of the byproduct above the minimal lower bound implied by physical feasibility. It is assumed that T_2 satisfies costly disposability with respect to pollution so that

$$\langle x, y, z\rangle \in T_2 \wedge \bar{z} \geq z \implies \langle x, y, \bar{z}\rangle \in T_2.$$

Thus, this non-conventional definition implies some *minimal* feasible vector of residuals for a given combination of inputs/intended outputs[14] so that the function $g(z, x_\imath)$

[14] In a manner similar to how much of the conventional literature on modeling intended output production utilizes production functions defining the *maximal* feasible set of output vectors associated with a fixed input bundle.

defines the minimum level[15] of bad outputs generated by a given level of input usage and satisfies

$$g_{x_\imath}(z, x_\imath) \leq 0 \;\; \forall \;\; \imath = 1 \ldots I'$$

$$g_z(z, x_\imath) \geq 0 \;\; \forall \;\; k = 1 \ldots K$$

to reflect the fact that increases in input usage associate with bad output production will increase this minimal amount. However, notice that T_2 violates standard free disposability of inputs that are associated with pollution and satisfies a completely different condition with respect to these inputs:

$$\langle x_{-\imath}, x_\imath, y, z \rangle \in T_2 \wedge \bar{z} \geq z \wedge \bar{x_\imath} \leq x_\imath \implies \langle x_{-\imath}, \bar{x_\imath}, y, \bar{z} \rangle \in T_2.$$

This condition reflects that fact that inefficiencies arising in the residual generation process imply that it may be possible to either reduce input usage to generate the same level of pollutant or reduce pollution generation for a given level of input usage.

Thus, we can infer that T_{BP} satisfies free disposability with respect to all intended outputs and inputs not associated with residual generation. However, the reduced form byproduction technology violates standard free disposability with respect to inputs associated with residual generation and satisfies costly disposability with respect to residual generation of pollutants.

[15]We could equivalently allow some function $\bar{g}$ to instead define the maximal level of byproduct feasible for a given input/intended output combination, but abstract from this issue here as it is not empirically binding in our estimation techniques.

As a preliminary discussion, let's first consider the implication associated with utilizing only one implicit production relation to model T_2, the pollution generating mechanism. Recall that the standard residual generation set is defined as[16]

$$T_2 = \left\{ \langle x_{-\imath}, x_\imath, y, z \rangle \in \mathbf{R}_+^{I+J+K} \;\middle|\; g(z, x_\imath) \geq 0 \right\},$$

where g is differentiable and vectors satisfying $g(z, x_\imath) = 0$ are (weakly efficient) points on the boundary of the technology set T_2. Any vectors satisfying $g(z, x_\imath) > 0$ are inefficient production vectors with respect to the frontier of T_2.

Next, consider an efficient vector $\langle \hat{x}, \hat{y}, \hat{z} \rangle$ such that $g(\hat{x}, \hat{y}, \hat{z}) = 0$ and $g_z(\hat{x}, \hat{y}, \hat{z}) > 0$. Then by the implicit function theorem[17], there exist neighborhoods $U \subseteq R_+^{I+J+K-1}$ and $V \subseteq R_+$ around $\langle \hat{x}, \hat{y}, \hat{z_{-k}} \rangle \in R_+^{I+J+K-1}$ and $\hat{z_k} \in R_+$ and a function $\varphi : U \to V$ such that

$$\hat{z_k} = \varphi(\hat{x}, \hat{y}, \hat{z_{-k}})$$

and

$$g(x, y, \varphi(x, y, z_{-k}), z_{-k}) = 0,$$

where z_{-k} is the vector z with the kth element purged.

[16]We abstract from including abatement output in this study as we lack data on abatement activities in our application. For a theoretical discussion including abatement output, see Murty, et. al. [2012].

[17]See Appendix.

The implied trade off between one pollutant and another along the efficient frontier is given by:

$$\frac{\partial \varphi(x, y, z_{-k})}{\partial z_{-k}} = -\frac{\frac{\partial g(x,z)}{\partial z_{-k}}}{\frac{\partial g(x,z)}{\partial z_k}} \leq 0 \quad \forall \quad k.$$

This implies that pollutants are substitutable for one another and that there exists a rich menu of $\langle z_k, z_{-k}\rangle$ for a given input and intended production vector, inconsistent with the physical and chemical processes that govern residual generation via materials balance since the residual generation mechanism may be specific to the utilization of particular inputs (ie: coal) and one combination of inputs may not be able to produce such a rich menu of unintended byproducts.

To reconcile the trade off problem, the residual generation set introduced in Murty, et. al. [2012] is further partitioned to allow for the independent generation of pollutants via multiple implicit production relations.

Another shortfall of Murty et. al.'s [2012] approach is that, while allowing for a decomposition of efficiency metrics between intended and unintended output production, it does not allow for the decomposition of such metrics across individual pollutants. That is, their specification of the technology allows for the computation of overall intended output efficiency and overall efficiency in pollution reduction, but the specification does not provide efficiency estimates for each pollutant individually. Perhaps most importantly, this paper makes a novel improvement in measurement by adjusting the model to allow for the joint estimation of decomposable efficiency scores for reductions in NO_x and SO_2 at the pollutant level.

3.2 A Generalized Extension

This section explains the extension of Murty et. al's [2012] model. The extended model utilizes a separate implicit production relation to govern the intended and unintended production of each y_j and z_k. For notational purposes, allow the input space to be partitioned so that $x = \langle x^j, x^{-j} \rangle \in \mathbf{R}^I_+$ where inputs x^j are associated with the production of the intended output y_j and inputs x^{-j} are not. Similarly, let $x = \langle x^k, x^{-k} \rangle \in \mathbf{R}^I_+$ partition the input space into the set of vectors x^k associated with the generation of byproduct z_k and x^{-k} which are inputs that do not cause the generation of byproduct z_k. It is possible that the partitions of the input space with respect to intended output y_j overlap with the corresponding partitions for another intended output $y_{j'}$ or unintended output z_k [18]

Now define, for each intended output y_j, a standard technology set T_j such that

$$T_j := \left\{ \langle x^j, x^{-j}, y, z \rangle \in \mathbf{R}^{I+J+K}_+ | f_j(x^j, y_j) \leq 0 \right\} \text{ for } j = 1 \ldots J,$$

where the functions f_j are continuously differentiable in all of their arguments.

It is assumed that T_j satisfies the standard free disposability conditions with respect to inputs and intended outputs so that

$$\langle x, y, z \rangle \in T_j \wedge \bar{x} \geq x \implies \langle \bar{x}, y, z \rangle \in T_j \;\; \forall\, j = 1 \ldots J,$$

$$\langle x, y, z \rangle \in T_j \wedge \bar{y} \leq y \implies \langle x, \bar{y}, z \rangle \in T_j \;\; \forall\, j = 1 \ldots J,$$

[18]Extreme cases where all inputs are associated with the production of all outputs can be generalized from the above specification. It is also possible that a subset of inputs that generate one output may also be responsible for generating another.

which imply the differential restrictions

$$f_{j_x}(x^j, y_j) \leq 0 \ \ \forall \ \ x^j \in \mathbf{R}_+^I \ \wedge \ \forall \ \ j = 1 \ldots J,$$

$$f_{j_y}(x^j, y_j) \geq 0 \ \ \forall \ \ j = 1 \ldots J.$$

For each unintended output z_k, define the residual generation set T_k so that

$$T_k := \left\{ \langle x^k, x^{-k}, y, z \rangle \in \mathbf{R}_+^{I+J+K} | g_k(x^k, z_k) \geq 0 \right\} \ \text{ for } \ k = 1 \ldots K,$$

where the functions g_k are continuously differentiable in all of their arguments.

It is assumed that T_k satisfies costly disposability with respect to byproducts so that

$$\langle x, y, z \rangle \in T_k \wedge \bar{z} \geq z \implies \langle x, y, \bar{z} \rangle \in T_k \ \ \forall \ \ k = 1 \ldots K,$$

so that the function $g_k(x^k, z_k)$ defines the minimum level[19] of bad outputs generated by a given level of input usage. T_k also satisfies the polar opposite condition of free disposability with respect to byproduct-generating inputs

$$\langle x^k, x^{-k}, y, z \rangle \in T_k \wedge \bar{z} \geq z \wedge \bar{x_k} \leq x_k \implies \langle x_{-k}, \bar{x_k}, y, \bar{z} \rangle \in T_k.$$

The differential restrictions implied by these properties of the residual generation mechanisms are given by

$$g_{k_x}(x^k, z_k) \leq 0 \ \ \forall \ \ x^k \in \mathbf{R}_+^I \ \ \wedge \ \ \forall \ \ k = 1 \ldots K,$$

[19] We could equivalently allow some function $\bar{g}$ to instead define the maximal level of byproduct feasible for a given input/intended output combination, but abstract from this issue here as it is not empirically binding in our estimation techniques.

$$g_{k_z}(x^k, z_k) \geq 0 \;\; \forall \;\; k = 1 \ldots K.$$

The extended byproduction technology is then defined as the intersection of the intended production sets and the residual generation sets

$$T_{BP}^{EX} := \left\{ \cap T_j \right\}_{j=1}^{J} \cap \left\{ \cap T_k \right\}_{k=1}^{K}$$
$$= \left\{ \langle x, y, z \rangle \in \mathbf{R}_+^{I+J+K} | f_j(x^j, y_j) \leq 0 \;\wedge\; g_k(x^k, z_k) \geq 0 \;\forall\; j = 1 \ldots J \;\wedge\; \forall\; k = 1 \ldots K \right\}.$$

4 The Data, DEA Estimation, and Efficiency Measurement

The first part of this section describes the data used in the analysis. The next section derives DEA estimates for the byproduction technologies for the parameters of the given data. The third section describes the construction of productivity indexes and the specific metrics utilized for the joint production system of good and bad outputs.

4.1 Description of the Data

Observations from 92 coal-fired power plants from the years 1985 through 1995 are used to construct the efficiency indexes and to estimate the byproduction technology.[20] A summary of the data can be found in table [INSERT TABLE HERE]. Each decision making unit (DMU) is a coal-fired electrical plant producing one intended output, net electrical generation (y), measured in kWh, and two byproducts, sulfur dioxide (SO_2)

[20]A big thanks to Carl Pasurka for providing access to the data.

and nitrogen oxides (NO_x), measured in short tons (z_1 and z_2). The inputs used by each plant consist of the capital stock, the number of employees, and the heat content of coal, oil, and natural gas, measured in Btus (x_1, x_2, x_3, x_4 and x_5, respectively).[21] In order to model homogeneous production technologies via data envelopment, coal must provide a minimum of 95 % of the Btu of fuels consumed by each plant.[22]

The number of employees is calculated as an average taken from data in the U.S. Federal Energy Regulatory Commission Form 1 survey. Additionally, the FERC 1 survey also collects information on the historical cost of plants and equipment and does not consider investment expenditures. Thus, variation in the value of plants and equipment reflect the value of additional plant and equipment less the value of depreciated plant and equipment. In constructing the capital stock in each period for each plant, this study assumes that changes in the costs of plants and equipment reflect net investment.[23] Past costs are converted to same-period dollar values via the HWI,[24] The net constant dollar capital stock is then the sum of the ratios of net investment to HWI over all previous years. Thus, in the first year of operation, the net investment of a power plant is equal to the aggregate value of its plant and

[21] This study ignores the consumption of fuel inputs other than coal, oil, and natural gas if the consumption of these fuel inputs constitutes less than .0001 % of a plant's total fuel consumption.

[22] Otherwise, the firm is not considered to be a coal-fired electric plant. DEA assumes that technologies are homogeneous across decision making units. See Pasurka [2006] for similar treatment.

[23] Yaisawarng and Klein [1994], Carlson et al. [2000], and Pasurka [2006] are studies that also measure the capital stock in the same capacity.

[24] See Whitman, Requardt, and Associates, LLP [2002]

equipment.

The U.S. Department of Energy's Form EIA-767 survey provides the information on fuel consumption and net electrical output, which is utilized to derive estimates of SO_2 and NO_x emissions.[25]

Moreover, table [INSERT TABLE HERE] lists the coal-fired plants by name and identifies those that were required to comply with the mandated emissions reductions, which were announced in 1990 and became binding in 1995. Data on which firms were required to comply with the mandated Phase I SO_2 reductions was found at the Environmental Protection Agency's website http://www.epa.gov/air/caa/title4.html.

4.2 Constructing the DEA Technologies

In the application herein, the extended byproduction technology is modeled as the intersection of three production sets: one that governs the intended production of electrical generation, and two that independently model the residual generation of pollutants, NO_x and SO_2. Input vectors are denoted by $x \in \mathbf{R}^5_+$, intended output vector by $y \in \mathbf{R}^1_+$, and unintended output (byproducts) vector by $z \in \mathbf{R}^2_+$. For the application herein, it is assumed that the set of fuel inputs $\langle x_3, x_4, x_5 \rangle = x^k$ for $k = 1, 2$ are associated with the residual generation of both emissions[26] and that all

[25] A common criticism of DEA in this type of environment is that it does not consider measurement error, of which there most likely is in deriving emissions estimates based on observables in the production process.

[26] More generally, there is no reason that the set of inputs generating one pollutant are the same as the set of inputs that generate a different pollutant, and this model can handle this case as well

five inputs are associated with the production of electrical generation so that $x^j = x$. The extended byproduction technology is then defined as

$$T_{BP} = T_E \cap T_{SO_2} \cap T_{NO_x}$$

where

$$T_E = \left\{ \langle x, y, z \rangle \in \mathbf{R}_+^{I+J+K} \mid f(x, y) \leq 0 \right\},$$

$$T_{SO_2} = \left\{ \langle x, y, z \rangle \in \mathbf{R}_+^{I+J+K} \mid g_1(x_3, x_4, x_5, z_1) \geq 0 \right\},$$

$$T_{NO_x} = \left\{ \langle x, y, z \rangle \in \mathbf{R}_+^{I+J+K} \mid g_2(x_3, x_4, x_5, z_2) \geq 0 \right\}.$$

Under the assumption of convexity and constant returns to scale[27], the DEA technologies are constructed by enveloping the input-output data in the tightest fitting convex set, an n-dimensional polyhedral cone. A benefit of DEA is that it is a nonparametric technique so that the estimated frontier is completely data driven with minimal assumptions regarding the functional form of the production relations. The construction of the DEA technologies requires the following elements:

(i) D decision making units (DMUs), indexed by d. In this case, each coal-fired plant.

(ii) J intended outputs, indexed by j, with quantity vector $y \in \mathbf{R}_+^J$. Let Y be the $D \times K$ matrix of intended output observations.

provided the modeler is able to identify such a partition in the input space. A priori, there is no reason to assume that is the case in this study but allow for it.

[27]The analysis is also robust to allowing for variable returns and non increasing returns, so only the CRS results are reported.

(iii) I inputs, indexed by i. The last I' are inputs associated with causing pollution and belong to partition x^k. The remaining $I - I'$ inputs are non pollution-generating and belong to partition x^{-k}. The quantity vector is $x = \langle x^k, x^{-k}, \rangle$. The $D \times I$ matrix of input observations is then partitioned into $X = \langle X^k, X^{-k}, \rangle \in \mathbf{R}_+^I$.

(iv) K pollutants indexed by k, with quantity vector $z \in \mathbf{R}_+^K$. Let Z be the $D \times K$ matrix of pollution observations.

In our analysis, $D = 92$, $J = 1$, $I = 5$, $I' = 3$, $K = 2$.

The DEA byproduction technology is constructed in four stages.

(i) T_E^{DEA} is constructed by

$$T_E^{DEA} = \{\langle x, y, z \rangle \in \mathbf{R}_+^{I+J+K} | \lambda X \leq x \wedge \lambda Y \geq y \text{ for some } \lambda \in \mathbf{R}_+^D\}.$$

(ii) $T_{SO_2}^{DEA}$ is constructed by

$$T_{SO_2}^{DEA} = \{\langle x^k, x^{-k} y, z \rangle \in \mathbf{R}_+^{I+J+K} | \mu X^k \geq x^k \wedge \mu Z_1 \leq z_1 \text{ for some } \mu \in \mathbf{R}_+^D\}.$$

(iii) $T_{NO_x}^{DEA}$ is constructed by

$$T_{NO_x}^{DEA} = \{\langle x^k, x^{-k} y, z \rangle \in \mathbf{R}_+^{I+J+K} | \nu X^k \geq x^k \wedge \nu Z_2 \leq z_2 \text{ for some } \nu \in \mathbf{R}_+^D\}.$$

(iv) The DEA byproduction technology T_{BP}^{DEA} is defined as the intersection of T_E^{DEA}, $T_{SO_2}^{DEA}$, and $T_{NO_x}^{DEA}$.

$$T_{BP}^{DEA} = \{\langle x^k, x^{-k} y, z \rangle \in \mathbf{R}_+^{I+J+K} | \lambda [X^k \quad X^{-k}] \leq \langle x^k, x^{-k} \rangle$$

$$\wedge \; \lambda Y \geq y \quad \wedge \quad \mu X^k \geq x^k \quad \wedge \quad \mu Z_1 \leq z_1 \quad \wedge \quad \nu X^k \geq x^k \quad \wedge \quad \nu Z_2 \leq z_2$$

$$\text{for some } \langle \lambda, \mu, \nu \rangle \in \mathbf{R}_+^{3D}\}.$$

4.3 Distance Metrics and Productivity Indexes

This section discusses the calculation of efficiency (inefficiency) in production by crediting a power plant for expansions in intended electrical generation and contemporaneous contractions in pollutants. It is assumed that there is no technological regress so that if a production vector is feasible at time t then it is also feasible at time $\tau > t$. This implies that, over time, the technology sets only increase in size, are non-imploding, and are estimated by using all past (but not future) observations as feasible production vectors[28]. Efficiency in intended output (electrical generation) is calculated using the standard hyperbolic index by solving the following optimization problem:

$$D^{E}_{HYP}(x, y, z, T_E) := \min_{\alpha>0}\{\alpha | \langle x, y/\alpha, z\rangle \in T_E\}$$

The non-linear problem can easily be converted into a linear maximization problem with an identical solution set using DEA. For each decision making unit d' and each

[28]Computations for the indexes are also done where the technology in period t is constructed by using observations only from period t, $t-1$, and $t-2$ in a three year rolling window which is also standard treatment in the literature. See Pasurka [2006] for an example using the rolling window technology. Results are robust to this formulation of the technology and are not reported.

period τ, solve:

$$[D_{HYP}^{E,d',\tau}(x,y,z,T_E)]^{-1} := \alpha^{-1} = \max_{\delta,\lambda} \delta \qquad \text{s.t.}$$
$$\sum_{t=1}^{\tau}\sum_{d=1}^{D}\lambda_{d,t}y_{d,t} \geq \delta y_{d',t}$$
$$\sum_{t=1}^{\tau}\sum_{d=1}^{D}\lambda_{d,t}x_{d,t}^{i} \leq x_{d',t}^{i} \quad \forall i = 1\dots 5$$
$$\lambda \geq 0$$

$D_{HYP}^{SO_2}(x,y,z,T_{SO_2})$ measures the efficiency in reductions of SO_2 and is calculated by solving

$$D_{HYP}^{SO_2}(x,y,z,T_{SO_2}) = \min_{\beta>0}\{\beta|\langle x,y,\beta z\rangle \in T_{SO_2}\}$$

This index is computed via DEA by solving the following programming problem. For each decision making unit d' and each period τ, solve:

$$[D_{HYP}^{SO_2,d',\tau}(x,y,z,T_{SO_2})] := \min_{\beta,\mu} \beta \qquad \text{s.t.}$$
$$\sum_{t=1}^{\tau}\sum_{d=1}^{D}\mu_{d,t}z_{1,d,t} \leq \beta z_{1,d',t}$$
$$\sum_{t=1}^{\tau}\sum_{d=1}^{D}\mu_{d,t}x_{d,t}^{i} \geq x_{d',t}^{i} \quad \forall i = 3\dots 5$$
$$\mu \geq 0$$

Analogously, $D_{HYP}^{NO_x}(x,y,z,T_{NO_x})$, the measure of efficiency in reductions of NO_x emissions is calculated by solving

$$D_{HYP}^{NO_x}(x,y,z,T_{NO_x}) := \min_{\gamma>0}\{\gamma|\langle x,y,\gamma z\rangle \in T_{NO_x}\}$$

This index is computed via DEA solving the following programming problem: For each decision making unit d' and each period τ, solve:

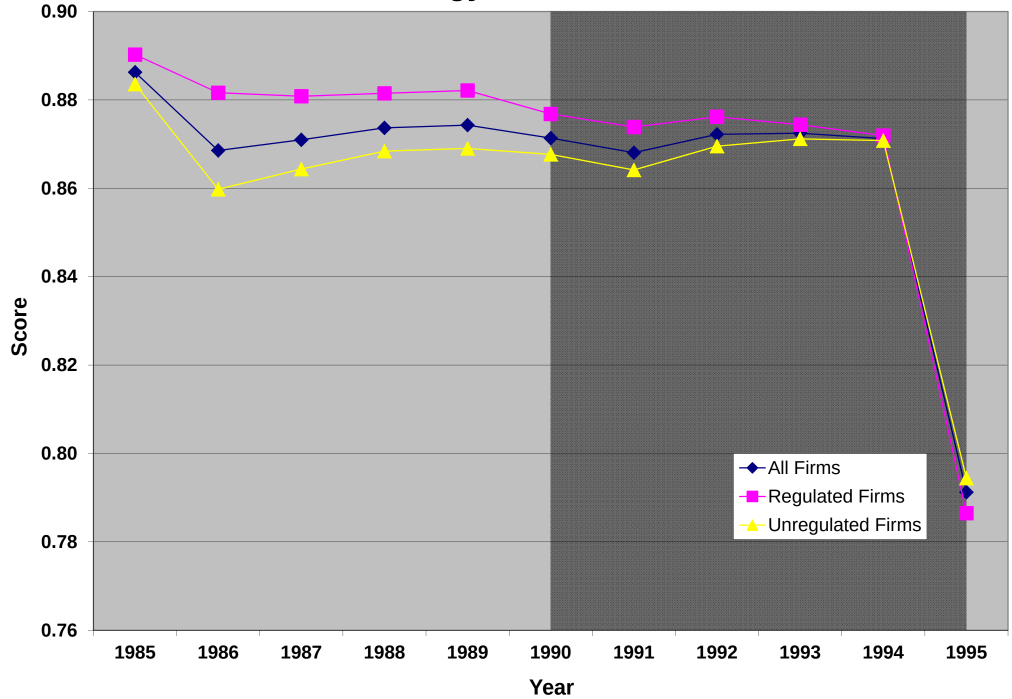
$$\begin{aligned}
[D_{HYP}^{NO_x,d',\tau}(x,y,z,T_{NO_x})] := \min_{\gamma,\nu} \gamma \qquad & \text{s.t.} \\
& \sum_{t=1}^{\tau}\sum_{d=1}^{D} \nu_{d,t} z_{2,d,t} \leq \gamma z_{2,d',t} \\
& \sum_{t=1}^{\tau}\sum_{d=1}^{D} \nu_{d,t} x_{d,t}^{i} \geq x_{d',t}^{i} \quad \forall i = 3\ldots5 \\
& \nu \geq 0
\end{aligned}$$

Note the distinct sets of multipliers $\langle \lambda, \mu, \nu \rangle$ used to capture the three production mechanisms independently.

5 Results

The time series of average efficiency scores for the regulated, unregulated, and all firms are show in Figures 1, 2, and 3 for electrical generation, SO_2 and NO_x reductions, respectively. There are several important patters that emerge. The next sections discusses the trends apparent in each. [INSERT CORRELATION TABLE]

Figure 1: Mean Intended Output Efficiency Scores Energy Production

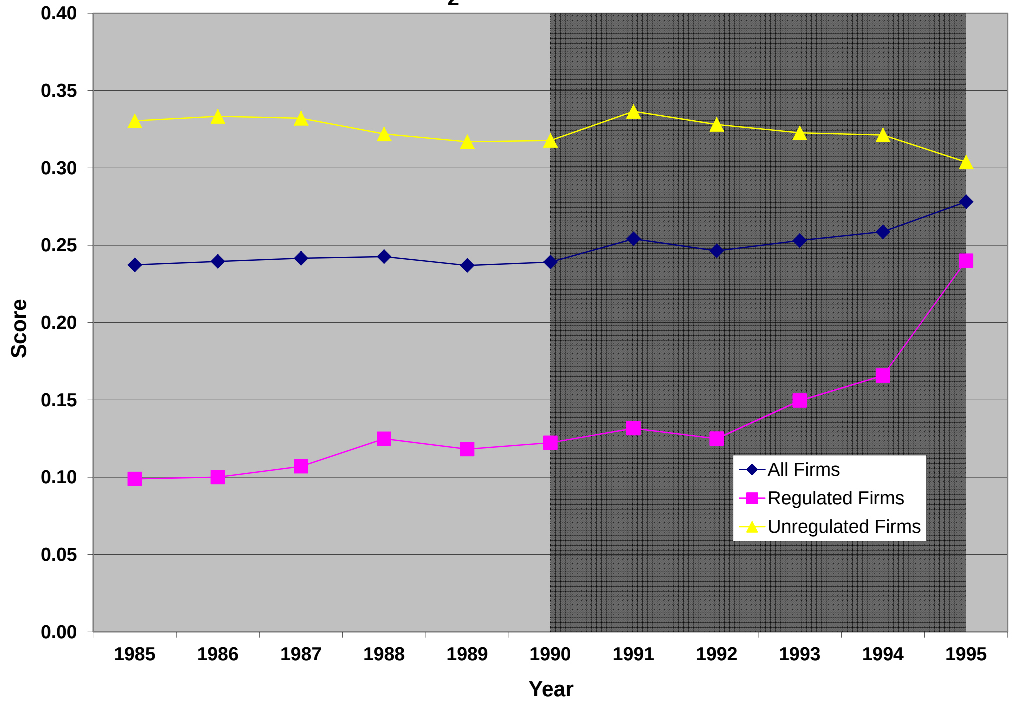


5.1 Efficiency in Electrical Capacity

By observing figure 1 from 1985-1994, average efficiencies in electrical generation across firms ranged from 66.25% (Edwardsport) to 100% (Harrington). Among the unregulated firms, the average efficiency in electrical generation ranged from 85.94%-88.36% over the same period, whereas the average efficiency in electrical generation for the regulated firms ranged from 87.19%-89.03%. This score can be interpreted as the percentage of potential output that a firm currently generates. Thus, a score of 90% means that a firm is producing 90% of what could be produced using that technology - a 10% loss in efficient capacity. Scores of 100% are for firms operating on the best practice frontier and they are weakly efficient in intended output production. Any firm with a score lower than 100% is operating with some inefficiency in electrical capacity.

During the 1985-1989 period, the regulated firms tended to out pace the capacity of unregulated firms by about 1.42% efficiency differential. However, subsequent to the 1990 policy announcement, this gap dropped significantly to .37%, an indication that the expectation of future binding abatement requirements caused the regulated firms to substitute efforts away from efficiently producing electricity to efficiently reducing emissions. Perhaps the most startling observation regarding the efficiency in electrical generation is the general collapse in efficiency that occurred in 1995, the year the mandated emissions reductions became binding. Note that in every year previous to 1995, the average efficiency in electrical generation for the regulated firms exceeded those of the unregulated firms. Only in 1995 does this relation flip. Moreover, the average efficiencies in 1995 were approximately 78.65% for regulated firms and 79.44% for the unregulated firms. Across all firms, the collapse in electrical generation averaged approximately an 8.17% reduction in the efficiency of capacity relative to the average efficiency over the 1985-1994 period prior. Those firms under binding regulation via Phase I of the ARR felt the brunt of the collapse in efficiency of capacity.

Figure 2: Mean Environmental Efficiency Scores
SO_2 Reductions

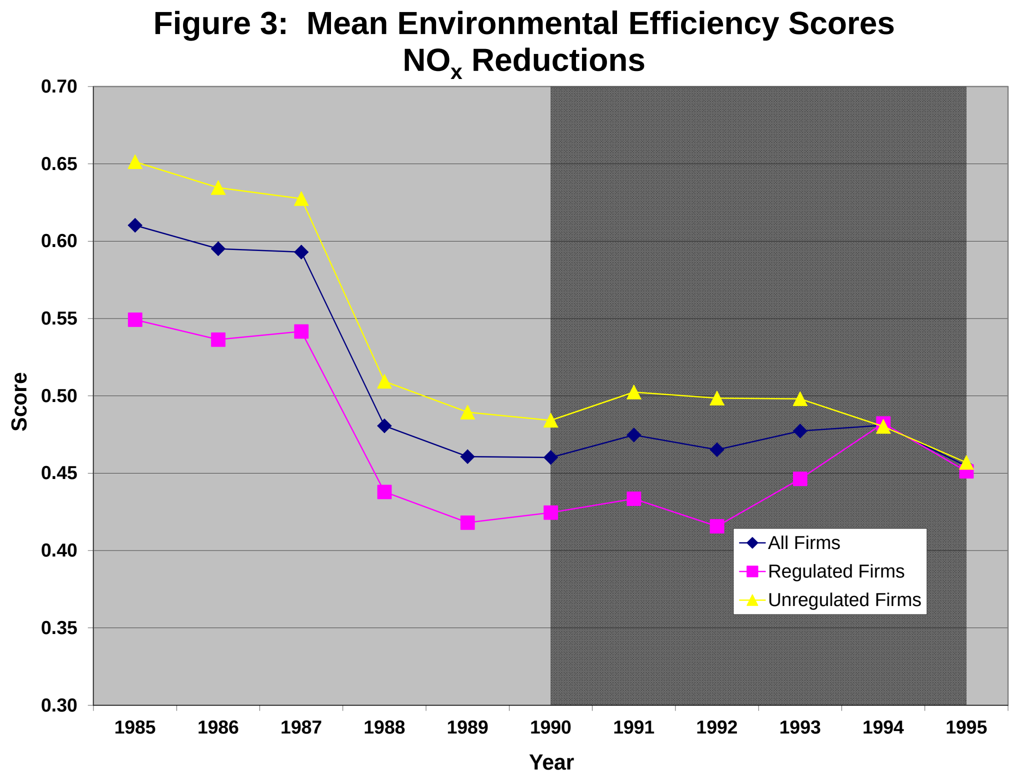


5.2 Efficiency in SO_2 Reductions

Figure 2 shows the time series of efficiency scores for reductions in SO_2 emissions. The interpretation of this score, which credits producers for retracting bad outputs, is the percent of current emissions level of the pollutant, in this case SO_2, that, if reached, would bring a firm to the efficient frontier with respect to reductions of that pollutant. For example, a firm with an index of 25% would be efficient in reducing that pollutant if they could cut 75% of current emissions so that only 25% of the current emissions would be generated. Again, a firm with a score of 100% would be on the efficient frontier for reducing SO_2 emissions. Any score lower than 100%

implies inefficiencies.

Another striking pattern emerges in Figure 2: for each year, the mean efficiency of the unregulated firms exceeds that of the regulated firms. The regulated firms averaged efficiencies from 1985-1989 ranged from 9.89%-12.49% prior to the policy change. Subsequent to the announcement, the average efficiency for regulated firms increased among the regulated firms to 12.23%-16.57%, and up to 24% in the 1995 period when the emissions reduction became binding .For the period of 1985-1989, the differential in emissions reductions between the regulated and unregulated firms was on average, 21.71%. From 1990-1995, this gap closed to 16.6%. The efficiencies in reducing SO_2 emissions for the unregulated firms remained relatively stable over the sample period at around 32.41%.



5.3 Efficiency in NO_x Reductions

Oddly enough, during the sample period, the average efficiency in NO_x emissions was *reduced* across all firms, but again, the regulated firms on average, were always less efficient in reduction of NO_x in every year except 1994, as is observable in Figure 3. The interpretation of this index is analogous to that of the SO_2 efficiency index. During this period, efficiency scores for NO_x reductions ranged from 41.57%-54.93% for the regulated firms while they varied from 45.69%-65.14% for the unregulated firms across the same period.

6 Conclusion

This study not only implements a previous decomposition with a novel modeling philosophy for pollution-generating technologies, but it also contributes to the discussion of efficiency measurement when some outputs are not necessarily socially desirable. This study also shows that in general, firms face a serious trade off between efficiency in output generation and efficiency in emissions reductions. In our sample, firms sacrificed an 8.17% reduction in efficiency in electrical capacity for an increase in efficiency in reducing SO_2 by an additional 14.02%. During the same period, we saw a global reduction in efficiency in reducing NO_x, evidence that the firm not only faces a trade off of intended production to reduce a pollutant, but it also sacrifices efficiency in reducing other pollutants as well - evidence that abatement methods may not be easily substitutable across such pollutants. Moreover, this study provides some insight into the latent characteristics that may tend to direct attention to a firm as a candidate for regulation. On average, the firms that were required to comply with binding emissions reductions were ones that, prior to the policy change, were some of the least efficient in mitigating SO_2 while they were the most efficient in producing electrical capacity. Moreover, a strong negative correlation between intended output efficiency and efficiency in pollution reductions (across all permutations) is further indicative of this trade off - firms that tend to operate efficiently in electrical generation tend to operate inefficiently with respect to pollution reductions. Some more evidence that the firms, when maximizing an unrestricted profit function, tend to ignore any externalities they may cause in production under the assumption that there are significant costs associated with emissions reductions.

Appendix: The Implicit Function Theorem

Let $f : \mathbf{R}_+^n \times \mathbf{R}_+^m \to \mathbf{R}^m$ be a continuously differentiable vector valued function with image $f(x, y) = z$, where $x \in \mathbf{R}_+^n$ and $y \in \mathbf{R}_+^m$. Let $\langle \hat{x}, \hat{y} \rangle \in \mathbf{R}_+^{n+m}$ be such that $f(\hat{x}, \hat{y}) = 0$ and the $m \times m$ matrix $\nabla_y f(\hat{x}, \hat{y})$ is full-row ranked (has a non-zero determinant). Then there exist neighborhoods U and V around $\hat{x}$ and $\hat{y}$ in $\mathbf{R}_+^n$ and $\mathbf{R}_+^m$, respectively, and a continuously differentiable function $\phi : U \to V$ with image $\phi(x) = y$ such that, for all $x \in U$, we have $f(x, \phi(x)) = 0$ and

$$\nabla_x \phi(x) = - \left[\nabla_y f(x, \phi(x))\right]^{-1} \nabla_x f(x, \phi(x)).$$

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