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Potential gains from trading bad outputs: The case of U.S. electric power plants☆

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ABSTRACT

Jointly with kilowatt-hours (kWh), electric power plants also produce CO_2, NO_x, and SO_2. In this paper, we apply an environmental production model based on data envelopment analysis (DEA) to compare the production of kWh under command-and-control regulation of the undesirable byproduct with tradable permit regulation of the byproduct. This is done for each of the three undesirable outputs and combinations of them. We apply our model to a dataset of 80 coal-fired electric power plants from 1995 to 2005. From this we can identify the potential gains from trading the most common undesirable outputs produced by coal-fired electric power plants.

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1. Introduction

For most of the history of regulating undesirable byproducts of economic activity, the United States implemented its regulations using a command-and-control approach. An early exception was the introduction of a “bubble” in 1979. This policy allowed a producer to increase emissions from a source

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if it simultaneously reduced emissions by an equivalent amount from another source. Using a mathematical programming model, Atkinson et al. (1982) investigated variations in outcomes for bubbles under different permit designs for particulates. In a subsequent paper, Atkinson et al. (1991) investigated why there were fewer trades and smaller cost savings than had been anticipated at the onset of the bubble program. They found the sequential nature of the process of trading emission reduction credits under the bubble program was a key factor explaining the divergence of observed behavior from the initial expectations.

The best known market-based regulatory strategy was initiated with the enactment of the 1990 Clean Air Act Amendments that set the stage for the use of a tradable permit system to achieve a reduction in SO_2 emissions at minimal cost. One concern that emerged was the extent to which tradable permit programs do not attain complete minimization of pollution abatement costs. Färe et al. (2013) addressed this concern by calculating the existence of unrealized gains from trade under the SO_2 tradable permit program. First, they calculated the maximum good output production for each power plant subject to its observed vector of technology and inputs. Then, they calculated the potential increase in good output production for a sample of coal-fired power plants when the individual plants were allowed to adjust their bad output production subject to the constraint that bad output production for the entire sample could not increase. Finally, calculating the ratio of maximum good output production when the bad outputs are tradable to the maximum good output production when bad outputs are not tradable allowed them to identify the extent of unrealized gains from trade for each power plant. Using this approach, less efficient regulatory strategies come at the cost of reduced good output production. Hence, this model represents a good output-oriented perspective on the cost of unrealized gains from trade**.**

Färe et al. (2014) specified an input-oriented (or more specifically a labor-oriented) perspective on regulatory rigidities.[1] Instead of maximizing good output production and identifying unrealized increases in good output production, they minimized labor use and identified regulatory inefficiencies via differences in employment. For a fixed technology and output vector, less efficient regulations increase the labor requirements of electric power plants.

Färe et al. (2013, 2014) specified models with one tradable bad output. In this paper, we extend these models by investigating the potential gains from trade when multiple bad outputs – CO_2, NO_x, and SO_2 – are traded.

Previous studies have modeled production technologies with multiple bad outputs. Burtraw et al. (2003) specified a multiple bad output framework to identify the ancillary (or co-benefits) of reducing CO_2 emissions in the electricity sector. Färe et al. (2012) specified a quadratic directional distance function to estimate the elasticities of transformation between SO_2 and NO_x emissions of coal-fired power plants in order to identify the extent to which the bad outputs are substitutes or complements. If the bad outputs are complements then there are ancillary benefits from policies targeted at reducing one of the bad outputs. Agee et al. (2013) also proposed a quadratic directional distance function to estimate the association among SO_2, NO_x, and CO_2 emissions of 77 electric utilities.

We calculate the maximum kilowatt hour (kWh) production of each plant with its observed level of bad output production, which generates a baseline value after the elimination of technical inefficiency that we refer to as the command-and-control simulation. We then calculate maximal kWh for all plants if the observed SO_2, NO_x, and CO_2 emissions are optimally allocated among plants via a tradable permit system. We refer to this as the tradable permit simulation. The ratio of plant kWh between the second and first simulations, represents the change in output for each plant if an efficient tradable permit program is implemented. The final step is calculating the sum of maximal kWh for all plants - the industry output – under both the command-and-control and tradable permit simulations, which yields the *potential* gains from trade with an efficient tradable permit system.

While there have been several studies that model the cost of reducing multiple bad outputs, this paper represents to our knowledge the first attempt to model gains from tradable permit regulatory

[1] With constant returns to scale, an output-oriented measure of efficiency expands all outputs proportionately with a given input vector and yields the same efficiency results as an input-oriented efficiency measure that seeks to contract all inputs proportionately for a given output vector.

strategies when multiple bad outputs are simultaneously traded. For those bad outputs (NO_x and SO_2) whose production is already subject to tradable permit regulatory systems, the results highlight unrealized gains from the existing tradable permit systems. Of the plants in our sample, some participated in the tradable permits program for SO_2 during 1995–1999 and all participated during 2000–2005.[2] For the bad output (CO_2) not being traded, the results identify potential gains from implementing a tradable permit scheme. When simultaneously modeling two or three bad outputs, the effects of the synergies in the abatement processes on the potential gains from trade can be estimated.

We apply our model to a balanced panel dataset of 80 coal-fired electric power plants from 1995 to 2005, where the good output is kWh and bad outputs are emissions of CO_2, NO_x, and SO_2. The inputs consist of the capital stock, the number of employees, and the heat content (in Btu) of coal, oil, and natural gas consumed at each power plant.

To estimate the impact of regulation we apply an environmental production model based on activity analysis or data envelopment analysis (DEA), using basic linear programming (LP) techniques. Our paper estimates the potential gains from trade (i.e., increased kWh production) for an industry if an efficient tradable permit system is implemented.

The remainder of this study is organized in the following manner. In Section 2, we define the opportunity cost of regulations in terms of an environmental production function and its associated LP programs. In Section 3, the data and results are presented, and Section 4 summarizes this study.

2. The models

In this paper, we have one $y \geq 0$ desirable output (kWh), and three undesirable outputs $u = (u_1, u_2, u_3) \in \Re_+^3$, CO_2, NO_x, and SO_2. The inputs are capital stock, the number of employees, and the heat content (Btu) of coal, oil, and natural gas, i.e., $x = (x_1, \ldots, x_5 \in \Re_+^5)$. The data are available for each power plant $k = 1, \ldots, K$ and time period $t = 1, \ldots, T$

$$(x^{k,t}, y^{k,t}, u^{k,t}) \in \Re_+^{N+1+J}, \quad t = 1, \ldots, T \, (\text{where } N = 5 \text{ and } J = 3)$$

From these data, we create a common production technology for all plants at each time period using activity analysis or equivalently DEA. Here we represent it by its output sets. For plant k' at time t it takes the form

$$P^t(x_{k'}^t) = \{(y^t, u^t): \begin{array}{l} \sum_{k=1}^{K} z_k^t y_k^t \geq y_{k'}^t \\ \sum_{k=1}^{K} z_k^t u_{kj}^t = u_{k'j}^t, \quad j = 1, 2, 3 \\ \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t, \quad n = 1, \ldots, 5 \\ Z_k^t \geq 0 \end{array} \tag{1}$$

The intensity variables z_k^t, which create the technologies based on the data, are restricted to be non-negative. Here the inputs are given at $x_{k'n}^t$ and the set of all feasible (y,u) are constructed as the convex combinations of the observed data (on the left-hand-side of the constraints). This implies that the technology exhibits constant returns to scale, i.e., (dropping the t and k')[3]

$$P(\lambda x) = \lambda P(x), \quad \lambda \geq 0.$$

[2] During 2004–2005, some plants in our sample participated in the NO_x SIP Call program.

[3] Although Färe et al. (1986) demonstrated how to impose a variable returns to scale (VRS) technology when modeling the joint production of good and bad outputs, in this paper we assume constant returns to scale.

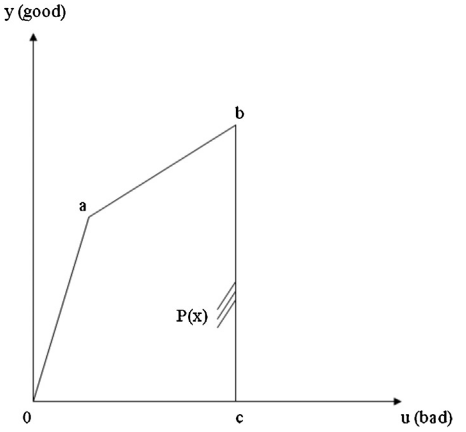

Fig. 1. An environmental output set.

The inequality in the expression for the desirable output, y, makes this output strongly disposable, i.e.,

$$\text{if}\,(y,\,u) \in P(x)\,\text{and}\,y' \leq y\,\text{then}\,(y',\,u) \in P(x).$$

In other words, the producer can freely dispose of that output.

The equalities for the undesirable outputs together with the inequality for y, makes the (y,u) weakly disposable, i.e.,

$$(y,\,u) \in P(x)\,\text{and}\,0 \leq \theta \leq 1 \geq (\theta y,\,\theta u) \in P(x).$$

In other words, for an observation of good and bad outputs (y,u) its proportional contraction is feasible (i.e., belongs to the output set $P(x)$). Imposing weak disposability corresponds to the case when production of the bad output is regulated, i.e. given input level x, bad output reduction is costly in the sense that it requires reduction of the good output. The inputs are strongly disposable,

$$\text{if}\,(y,\,u) \in P(x)\,\text{and}\,x' \geq x\,\text{then}\,(y,\,u) \in P(x').$$

We also impose nulljointness between good and bad outputs,[4]

$$\text{if}\,(y,\,u) \in P(x)\,\text{and}\,u = 0\,\text{then}\,y = 0,$$

which assumes producing good outputs results in bad outputs being produced as byproducts.[5]

This condition can be tested from the data, in the sense that the conditions

$$\sum_{k=1}^{K} u_{kj} > 0 \quad j = 1, 2, 3$$

$$\sum_{k=1}^{3} u_{kj} > 0 \quad k = 1, \ldots, K$$

must hold. The data support these inequalities. The data also supports conditions that make $P(x)$ a compact set (closed and bounded).[6]

[4] Førsund (2009) and Murty et al. (2012) investigated the implications of joint production models excluding material balance conditions.

[5] Baumgärtner et al. (2001) discuss the relation between joint production and thermodynamics.

[6] See e.g., Färe and Grosskopf (2004).

An illustration of a typical output set satisfying the above conditions is Fig. 1, which we term an "environmental output set." The output set for the environmental technology for a and b in Fig. 1 is bounded by 0*abc*0. Suppose we have two firms, both with given levels x, one producing the output bundle at a and the other at b. The fact that the technology intersects the y axis at zero is consistent with null jointness. Therefore, each input vector x produces an output set $P(x)$, which consists of combinations of good and bad outputs (y,b). By imposing the assumption that good and bad outputs (y,b) are together weakly disposable, we assume it is "costly" to reduce the bad outputs. Hence, for a given technology and input vector a producer must forgo production of some good output if it wants to reduce its bad outputs, either directly by reducing production or indirectly by assigning some of the given input vector to abatement activities. Thus, weak disposability allows us to model the opportunity cost of reducing the bad output(s), which appears in the figure as the segment 0*ab*.

As a baseline, we begin by simulating a command-and-control regime and its opportunity cost in terms of lost good output, which can be done by solving

$$\hat{y}^t_{k'} = \max \tilde{y}^t_k \quad s.t. (\tilde{y}^t_k, u^t_{k'}) \in P^t(x^t_{k'})$$

for each plant. The $\hat{y}^t_{k'}$ denotes the maximal output when inputs and bad outputs are fixed as observed.[7] From a regulation point of view, this can be seen as a command-and-control problem. The plant is given its observed production of bad outputs which it cannot exceed. One may also solve the efficiency problem for all plants jointly, namely as the solution to the following problem:

$$\begin{aligned}
Y^{CC} = \quad & \max_{\tilde{y}^t, z^t} \sum_{k=1}^{K} \tilde{y}^t_k, \quad \text{for each} \quad t = 1, \ldots, T \\
& \text{Power Plant 1} \\
s.t \quad & \sum_{k=1}^{K} z^{1t}_k y^t_k \geq \tilde{y}^t_1 \\
& \sum_{k=1}^{K} z^{1t}_k u^t_{kj} \leq u^t_{1j}, \quad j = 1, \ldots, 3 \\
& \sum_{k=1}^{K} z^{1t}_k x^t_{kn} \leq x^t_{1n}, \quad n = 1, \ldots, 5 \\
& z^{1t}_k \geq 0, \quad k = 1, \ldots, K \\
& \vdots \\
& \text{Power Plant } K \\
& \sum_{k=1}^{K} z^{Kt}_k y^t_k \geq \tilde{y}^t_K \\
& \sum_{k=1}^{K} z^{Kt}_k u^t_{kj} \leq u^t_{Kj}, \quad j = 1, \ldots, 3 \\
& \sum_{k=1}^{K} z^{Kt}_k x^t_{kn} \leq x^t_{Kn}, \quad n = 1, \ldots, 5 \\
& z^{Kt}_k \geq 0, \quad k = 1, \ldots, K
\end{aligned} \tag{2}$$

[7] The tilde (∼) over the y in (2) and over the y and u in (3) indicates these are variables.

This specification of (2) is equivalent to solving a separate LP problem for each power plant where the objective function seeks to maximize the good output production of that power plant subject to its bad output and input constraints. The piece-wise linear frontier for each observation k' is constructed from the K observations in each year. The optimum level of good output production must equal or exceed the good output of observation k' and the optimum level of bad output production must not exceed the bad output of observation k', while using no more of each input than observation k'. We introduced an inequality for the bad outputs to avoid the case when more of the good output can be produced by producing less of the bad output.[8]

This maximum, $Y^{CC} = \sum_{k=1}^{K} \hat{y}_k^t$, may be compared to the observed good outputs to yield an industry efficiency score:

$$\frac{\sum_{k=1}^{K} \hat{y}_k^t}{\sum_{k=1}^{K} y_k^t}.$$

This score can be computed for each time period $t = 1,\ldots,T$ to track its development.

Next we turn to our models which allow for industry-wide tradable permits. We begin with the model in which the first undesirable output is subject to industry-wide regulation. Here, we introduce an industry constraint which is set equal to the observed total bad output at t

$$\sum_{k=1}^{K} u_{k1}^t.$$

We then allow each plant to choose its $j = 1$ undesirable output so that the sum over all plants does not exceed the industry constraint. We denote the free (i.e., variable) $j = 1$ undesirable output by

$$\tilde{u}_{k1}^t$$

and hence we will have $\sum_{k=1}^{K} \tilde{u}_{k1}^t \leq \sum_{k=1}^{K} u_{k1}^t$

[8] In principle, the inequality could yield unbounded output sets. This can be avoided by setting the right-hand side equal to a bound such as the largest observed value of the bad. This is also done by Aparicio et al. (2013).

as our new restriction. This is introduced in (3) as the Aggregate Tradable Bad Output constraint. Thus, our problem becomes

$$
\begin{aligned}
Y_1^{TP} = \; & \max_{\tilde{y}^t, z^t, u^t} \sum_{k=1}^{K} \tilde{y}_k^t \quad \text{for each} \quad t = 1, \ldots, T \\
& \text{Power Plant 1} \\
s.t. \quad & \sum_{k=1}^{K} z_k^{1t} y_k^t \geq \tilde{y}_1^t \\
& \sum_{k=1}^{K} z_k^{1t} u_{k1}^t \leq \tilde{u}_{11}^t \\
& \sum_{k=1}^{K} z_k^{1t} u_{kj}^t \leq u_{1j}^t, \quad j = 2, 3 \\
& \sum_{k=1}^{K} z_k^{1t} x_{kn}^t \leq x_{1n}^t, \quad n = 1, \ldots, 5 \\
& z_k^{1t} \geq 0, \quad k = 1, \ldots, K. \\
& \vdots \\
& \text{Power Plant } K \\
& \sum_{k=1}^{K} z_k^{Kt} y_k^t \geq \tilde{y}_K^t \\
& \sum_{k=1}^{K} z_k^{Kt} u_{k1}^t \leq \tilde{u}_{K1}^t \\
& \sum_{k=1}^{K} z_k^{Kt} u_{kj}^t \leq u_{Kj}^t, \quad j = 2, 3 \\
& \sum_{k=1}^{K} z_k^{Kt} x_{kn}^t \leq x_{Kn}^t, \quad n = 1, \ldots, 5 \\
& z_k^{Kt} \geq 0, \quad k = 1, \ldots, K \\
& \text{Aggregate Tradable Bad Output} \\
& \sum_{k=1}^{K} \tilde{u}_{k1}^t \leq \sum_{k=1}^{K} u_{k1}^t
\end{aligned}
\tag{3}
$$

Denoting the maximum by

$$Y_1^{TP}$$

where "1" stands for the introduction of trading regulation of the first undesirable output. We may compute an industry score for $j = 1$ and t that compares output when trading to command-and-control:

$$\frac{Y_1^{TP}}{Y^{CC}} \tag{4}$$

We do the same for $j = 2,3$. When bad outputs are traded, the traded bad output constraint(s) and non-traded bad output constraint(s) in (3) are modified. In addition, the existence of two or three traded bad outputs requires a separate Aggregate Tradable Bad Output constraint for each traded bad output. For each Aggregate Tradable Bad Output constraint, the level of bad output production cannot exceed the industry bad output production in year t.

In summation, the command-and-control simulation (2) calculates the maximum industry electricity production when technical inefficiency is eliminated, while the tradable permit simulation (3) calculates the maximum industry electricity production when technical inefficiency and the suboptimal allocation of bads are eliminated and gains from trade are allowed.[9]

The difference in maximum good output production between the command-and-control simulation and tradable permit simulations constitute the potential good output production associated with eliminating regulatory rigidity (i.e., an efficient allocation of bad output production). For a fixed technology and input vector, more flexible (i.e., more efficient) regulations lead to increased good output production.

The interpretation of the results depends upon the existing regulatory strategy. If a command-and-control regulatory system exists, (2) – the command-and-control simulation – calculates the maximum industry good output production with the *observed* level of bad outputs for each power plant under the existing regulatory structure. The LP problem specified in (3), which is the tradable permit simulation, calculates the maximum industry good output if a tradable permit system is implemented. Hence, Y_j^{TP}/Y^{CC}, $j = 1, \ldots, 3$, represents the maximum increase in industry good output if an efficient spatial tradable permit system is implemented. If a tradable permit system exists, then (2) identifies the maximum good output production of each power plant with the *observed* level of bad outputs produced under the existing tradable permit system, while (3) calculates the maximum good output production if rigidities that limit trades of bad output permits under the existing tradable permit system were eliminated. Hence, Y_j^{TP}/Y^{CC} represents the maximum increase in industry good output if rigidities that limit bad output trades under the existing tradable permit system are eliminated.

3. Data and results

In the previous section, environmental production functions, which model the joint production of good and bad outputs, were introduced as a means of determining the distance between frontiers under trading and command-and-control. It was then possible to specify the environmental production functions as LP programs and calculate Y_j^{TP}/Y^{CC}, $j = 1, \ldots, 3$.

In this section we discuss the data used to implement the joint production model and the accompanying empirical results. Data from coal-fired power plants from 1995 to 2005 are used to solve the LP problems. The technology modeled in this study consists of one good output, "net electrical generation" (kWh), and three bad outputs: carbon dioxide (CO_2), nitrogen oxide (NO_x), and sulfur dioxide (SO_2). The inputs consist of the capital stock, the number of employees, and the heat content (in Btu) of coal, oil, and natural gas consumed at each power plant (there are separate constraints for each of the fuels). While the power plants may consume coal, oil, or natural gas, in order to model a homogeneous production technology, coal must provide at least 95% of the Btu of fuels consumed by each plant.[10] FERC Form 1 (http://www.ferc.gov/docs-filing/eforms/form-1/viewer-instruct.asp) is the source of labor and capital data for private electric power plants, while the EIA-412 survey (http://www.eia.doe.gov/cneaf/electricity/page/eia412.html) is the source of labor

[9] Because we do not incorporate the sulfur content of the fuel into our specification of the production technology, we are unable to identify the effects of fuel switching (i.e., a plant switches from high-sulfur to low-sulfur coal). Hence, the results of the tradable permit simulations reflect the net effect of trading permits and fuel switching.

[10] A number of plants consume fuels other than coal, oil, and natural gas (e.g., petroleum coke, blast furnace gas, coal-oil mixture, fuel oil #2, methanol, propane, wood and wood waste, and refuse, bagasse and other nonwood waste). In this study, any plant whose consumption of fuels other than coal, oil, and natural gas represented more than 0.0001% of its total fuel consumption (in Btu) is excluded. We ignore consumption of fuels other than coal, oil, and natural gas when these fuels represent less than 0.0001% of a plant's fuel consumption.

Table 1
Summary statistics.

	Units	Mean	Sample std. dev.	Maximum	Minimum
80 coal-fired power plants, 1995					
Electricity	kWh (in millions)	5711	4866	20,222	167
SO_2	short tons (in thousands)	40	40	192	2
NO_x	short tons (in thousands)	21	27	175	1
CO_2	short tons (in thousands)	6448	5428	25,669	237
Capital stock	dollars (in millions, 1973$)	290	195	863	57
Employees	workers	214	136	578	42
Heat content of coal	Btu (in billions)	57,064	47,174	193,574	2255
Heat content of oil	Btu (in billions)	109	116	514	0
Heat content of gas	Btu (in billions)	93	284	2083	0
80 coal-fired power plants, 2005					
Electricity	kWh (in millions)	6647	5249	22,338	176
SO_2	short tons (in thousands)	34	33	186	1
NO_x	short tons (in thousands)	12	9	39	1
CO_2	short tons (in thousands)	7011	5247	22,509	251
Capital stock	dollars (in millions, 1973$)	332	230	1009	59
Employees	workers	172	104	468	28
Heat content of coal	Btu (in billions)	66,877	51,036	215,802	2297
Heat content of oil	Btu (in billions)	108	129	738	0
Heat content of gas	Btu (in billions)	71	157	911	0

and capital data for public power plants.[11] In addition to the increasing number of private utilities not reporting capital and labor data, the DOE halted the EIA-412 survey after 2003 (http://www.eia.doe.gov/cneaf/electricity/page/eia412.html). However, the Tennessee Valley Authority voluntarily posted 2004–2006 data for its electric power plants on-line (http://www.tva.gov/finance/reports/index.htm).[12] The U.S. Department of Energy's (DOE) Form EIA-767 survey (see U.S. Department of Energy, various years) is the source of information about fuel consumption and net generation of electricity. The SO_2, NO_x, and CO_2 emission data are collected by the U.S. EPA as part of its Continuous Emissions Monitoring System (CEMS).

The sample consists of a balanced panel of 80 power plants for 1995–2005. Summary statistics for 1995 and 2005 are reported in Table 1. The period t technology consists solely of observations from period *t*.[13]

We operationalize our model by specifying the models in (2) and (3) with CO_2, NO_x, and SO_2 as the bad outputs. With three bad outputs – CO_2, NO_x, and SO_2 – we have eight sets of results. The model in (2) generates the command-and-control simulation results, while (3) generates seven sets of tradable permit simulation results. Three of these sets calculate the maximum good output (i.e., foregone good output) for the industry when only one of the bad outputs is traded. Three additional sets of results are generated by modeling different combinations when two of the bad outputs are

[11] Data on the cost of plant and equipment for years prior to 1981 were collected and published in annual reports from the Federal Power Commission and the Energy Information Administration. The Utility Data Institute (1999) is the source of the cost of plant and equipment data for 1981–1997. Finally, data for (1) the cost of plant and equipment and (2) employment collected by the FERC Form 1 for 1998–2005 and EIA-423 for 1998–2003 are downloaded from their respective websites.

[12] While both surveys collect data on the historical cost of plant and equipment, they do not collect data on investment expenditures. Hence, changes in the value of plant and equipment reflect the value of additional plant and equipment plus the value of retired plant and equipment. For this study, we assume changes in Cost of Plant reflect net investment (NI), which is the same assumption employed by Yaisawarng and Klein (1994, p. 453, footnote 30) and Carlson et al. (2000, p. 1322). We then convert the historical cost of plant data to constant dollar values using the Handy-Whitman Index (HWI) (see (Whitman, Requardt & Associates LLP, 2006). The net constant dollar capital stock (CS) for year n is calculated in the following manner: $CS_n = \sum_{t=1}^{n} \frac{NI_t}{HWI_t}$. In the first year of its operation, the net investment of a power plant is equivalent to the total value of its plant and equipment.

[13] The Appendix B contains a detailed discussion of the data. The LP problems are estimated using GAMS/MINOS. The appendix, data, and GAMS programs are available from the corresponding author upon request.

traded: (CO_2 and NO_x), (CO_2 and SO_2), and (NO_x and SO_2). Finally, we calculate the maximum good output for the industry when the three bads are traded.

Estimating the foregone gains from trade (i.e., foregone good output) for the industry requires modeling the command-and-control technology when the three bad outputs are not traded, and seven tradable permit cases when at least one of the bad outputs is traded. The command-and-control model imposes a separate constraint on each of the three bad outputs (bad outputs are not tradable), while the tradable permit model imposes an Aggregate Tradable Bad Output constraint (i.e., allow bad outputs to be tradable) for each bad output that is traded.

The models generate results for each of the 80 plants for each year in our sample. These results are aggregated and reported across time (i.e., we report arithmetic means for each plant) and across plants (i.e., we report arithmetic means for each year).

In Appendix A, Table A.1 reports the arithmetic means for the 1995–2005 results generated by calculating the ratio in (4) for each of the 80 plants in the sample. The values in Table A.1 provide information for each plant on the ratio of average maximum potential good output production when rigidities on bad output mobility are eliminated (i.e., tradable permit simulations) relative to average maximum potential good output production with no bad output mobility (i.e., command-and-control simulation), $(\sum_{t=1}^{T}\hat{\hat{y}}_k^t/\sum_{t=1}^{T}\hat{y}_k^t)$.[14] First, we examine the cases when regulatory rigidities are eliminated for a single bad output (columns 1–3) in Table A.1. Plants with declines in maximum potential good output production for the tradable permit simulation relative to the command-and-control simulation will report values less than unity in columns 1–3. Conversely, plants with values greater than unity in columns 1–3 experience an increase in maximum potential good output production for the tradable permit simulation relative to the command-and-control simulation. Finally, a plant with values of unity in columns 1, 2, or 3 experiences no change in its maximum potential good output production for the tradable permit simulation relative to the command-and-control simulation. Columns 4, 5, and 6 provide results when combinations of two bad outputs are simultaneously allowed to be traded, which increases mobility, while the values in column 7 provide results when all three bad outputs are simultaneously allowed to be traded. The results allow us to identify the net effect of a multiple bad output tradable permit system on the good output production of each plant. The interpretation of the results when multiple bad outputs are traded (i.e., regulatory rigidities are reduced for multiple bad outputs) is similar to when one bad output is traded. A value less than unity indicates the net effect of the tradable permit programs is to reduce the good output production of a plant, while a value greater than unity indicates the net effect of the multiple bad output tradable permit programs is to increase the good output production of a plant.

The net effect of the tradable programs results in Riverside (ID 1081) exhibiting the largest increase in good output production for the four cases when CO_2 is traded. Jim Bridger (ID 8066) has the largest increase in good output production when (1) SO_2 is the sole bad output traded and (2) when SO_2 and NO_x are both traded. H.F. Lee (ID 2709) reported the largest reductions in good output production for the three of cases when SO_2 and at least one additional bad output are traded.

The non-existence of a tradable permit program for CO_2 would lead to the expectation that the results for CO_2 should be higher due to the unexploited gains from trade. Interestingly, when allowing only one bad output to be traded, the bad output with the best known tradable permit program – SO_2 – shows higher foregone gains from trade than either NO_x or CO_2. Because the existence of the tradable permit program should leave only the missed opportunities for trades by the existing tradable permit system, this finding is surprising. These results may reflect the lack of any strategy to reduce CO_2 emissions other than reducing coal consumption. Hence, the close association between coal consumption and CO_2 emissions may be one explanation for these results.

Table A.2 reports the annual results for each of the seven cases. Fig. 2 provides a visual representation of trends in calculate changes in Y_j^{TP}/Y^{CC} for the cases when SO_2, NO_x, and CO_2 are the sole traded bad outputs.

While Table A.1 reports the ratio of average maximum potential good output production when eliminating rigidities on bad output mobility (tradable permit simulations) relative to average maximum

[14] $\hat{\hat{y}}_{k'}^t$ is the maximum good output produced by plant k′ with the tradable permit simulation in period t.

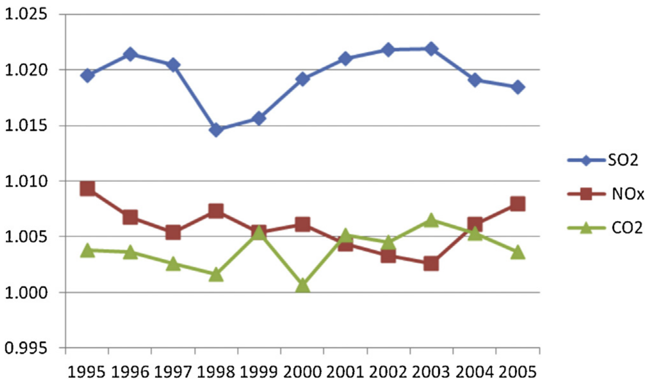

Fig. 2. $Y_j^{TP}/Y^{CC}, j=1,\ldots,3$.

good output production with no bad output mobility (command-and-control simulation) for individual plants ($\sum_{t=1}^{T}\hat{\hat{y}}_k^t/\sum_{t=1}^{T}\hat{y}_k^t$), the values in Table A.2 are generated using (4) and report the ratios for the industry ($Y_j^{TP}/Y^{CC}, j=1,\ldots,3$ which can be rewritten as $(\sum_{k=1}^{K}\hat{\hat{y}}_k^t/\sum_{k=1}^{K}\hat{y}_k^t)$). While good output production for *individual plants* can either increase or decrease when eliminating regulatory rigidities, the elimination of regulatory rigidities increases *industry* good output production. As a result, all values in Table A.2 must equal or exceed unity.

The ratios in Table A.2 reveal the increase in maximum potential good output production if regulatory rigidities associated with the bad outputs are eliminated.[15] The first three columns present results when a single bad output is allowed increased mobility among producers. The first column provides information on the potential increases in industry good output production during 1995–2005 if rigidities in the existing program of tradable permits for SO_2 could be eliminated, while the second the third columns reveal potential increases in industry good output production during 1995–2005 if tradable permit systems were implemented for NO_x and CO_2, respectively. Interestingly, the largest gains come from eliminating rigidities in the existing system of SO_2 tradable permits, instead of implementing new tradable permit systems for pollutants with no existing tradable permits.

Columns 4, 5, and 6 provide results when combinations of two bad outputs are simultaneously allowed increased mobility. As expected, the values in columns 4, 5, and 6 exceed the individual values of their component bad outputs reported in columns 1, 2, and 3. For example, the values in column 4 (SO_2 and NO_x) exceed the values in column 1 (SO_2) and column 2 (NO_x). However, it is interesting to compare the percent increase in good output in columns 4, 5, and 6 with the *sum* of the percent increase in good output for their components in columns 1, 2, and 3. This allows an examination of whether synergies exist when abating two or three bad outputs. For example, in 1999 the percent increase in column 4 (SO_2 and NO_x) is 2.54% while the sum of the percent increase in columns 1 (SO_2) and 2 (NO_x) is 2.11%. A majority of the results in Table A.2 show this same result – the sum of the component percent increase in good output is less than the percent increase in good output in columns 4, 5, and 6. Hence, in most cases good output increases more when two bad outputs are traded.

A similar set of calculations can be undertaken using the values in column 7, which provides results when all three bad outputs are simultaneously allowed increased mobility. First, the percent increase in good output in column 7 can be compared with the sum of percent increase in good output reported in columns 1, 2, and 3. Alternatively, the percent increase in good output in column 7 can be compared with the sum of percent increase in good output for each of the 2 bad output combinations (e.g., SO_2 and NO_x in column 4) and the percent increase in good output for the third bad output (e.g., CO_2 in

[15] Subtracting unity from the values in the table and multiplying by 100 yields the percent increase in good output with tradable permits relative to command-and-control.

column 3). In most instances, the results in Table A.2 reveal the sum of the percent increase in good output for the components is less than the percent increase in good output in column 7. Hence, in most cases good output increases more when three bad outputs are traded.

4. Conclusions

Previously, Färe et al. (2013) investigated trends in Y_j^{TP}/Y^{CC} with SO_2 as the sole traded bad output. In addition, Färe et al. (2014) specified an input-oriented (more specifically the labor-oriented) perspective by calculating the potential decrease in labor associated with eliminating unrealized gains from trade under the tradable permit system. In this paper, we extend the output oriented approach of Färe et al. (2013) and calculate the unrealized gains from trade for combinations of one, two, and three traded bad outputs.

The results indicate that the unrealized gains from trade under the existing SO_2 tradable permit system exceed the potential gains from implementing a tradable permit system for CO_2. While there might be potential gains from trade between the coal-fired power plants in our sample and other sources of CO_2 emissions (e.g., natural gas or oil power plants), implementing a system of tradable permits for CO_2 emissions among coal-fired power plants appear to generate few opportunities for increasing economic efficiency.

Appendix A.

Tables A.1 and A.2

References

Table A.1
Plant arithmetic means: $(\sum_{t=1}^{T}\hat{y}_k^t/\sum_{t=1}^{T}\hat{y}_k^t)$ for seven combinations of traded bad outputs (1995–2005) (bold = maximum value and bold and italics = minimum value).

Plant ID	SO_2	NO_x	CO_2	SO_2 and NO_x	SO_2 and CO_2	NO_x and CO_2	SO_2, NO_x, and CO_2
3	0.9960	0.9996	1.0007	0.9963	0.9985	1.0005	0.9963
8	0.9964	0.9997	1.0016	0.9945	0.9925	1.0033	0.9976
47	0.9974	1.0081	1.0000	1.0064	0.9939	1.0081	0.9978
50	1.0392	1.0015	1.0004	1.0395	1.0401	1.0033	1.0411
113	1.0892	1.0280	1.0000	1.1230	1.0892	1.0266	1.1255
469	1.0223	1.0000	1.0217	1.0223	1.0689	1.0216	1.0689
470	1.0011	1.0028	1.0020	1.0112	1.0060	1.0046	1.0243
477	1.0002	1.0000	1.0001	1.0002	1.0002	1.0012	1.0014
643	1.0002	1.0031	1.0002	1.0050	0.9991	1.0076	1.0085
703	1.0000	1.0000	1.0000	1.0000	1.0000	1.0059	1.0059
708	0.9994	1.0007	1.0028	0.9970	0.9999	1.0043	0.9972
727	0.9991	1.0003	1.0774	1.0007	1.0720	1.0818	1.0771
887	1.0022	1.0317	1.0000	1.0686	1.0022	1.0322	1.0747
988	0.9924	0.9989	1.0009	0.9931	0.9932	1.0014	0.9967
995	1.0821	0.9980	1.0058	1.0821	1.0896	1.0038	1.0896
1001	0.9976	**1.0608**	1.0000	1.0594	0.9956	1.0730	1.0717
1008	0.9882	1.0092	1.0074	0.9997	0.9965	1.0155	1.0009
1012	1.0274	1.0140	1.0100	1.0371	1.0449	1.0262	1.0530
1048	0.9992	1.0494	1.0131	1.0464	1.0130	1.0843	1.0906
1081	1.0217	1.0128	**1.1859**	1.0273	**1.2505**	**1.2713**	**1.3113**
1241	1.0617	0.9994	1.0061	1.0513	1.0567	1.0066	1.0587
1353	0.9986	1.0006	1.0106	0.9999	1.0035	1.0115	1.0040
1355	0.9979	1.0097	1.0002	1.0065	0.9969	1.0119	1.0079
1356	1.0544	1.0463	1.0041	1.0871	1.0546	1.0463	1.0847
1357	0.9970	0.9999	1.0090	0.9976	0.9977	1.0094	1.0023
1363	0.9935	1.0000	1.0542	0.9935	1.0520	1.0533	1.0537
1364	1.0229	1.0076	1.0175	1.0256	1.0535	1.0358	1.0744

Table A.1 (*Continued*)

Plant ID	SO_2	NO_x	CO_2	SO_2 and NO_x	SO_2 and CO_2	NO_x and CO_2	SO_2, NO_x, and CO_2
1378	1.0051	0.9998	1.0000	1.0029	1.0076	***0.9958***	1.0010
1379	1.0436	1.0033	1.0000	1.0421	1.0442	1.0029	1.0421
1733	1.0038	1.0002	1.0025	1.0062	1.0053	1.0103	1.0139
1743	1.0055	1.0023	1.0111	1.0093	1.0173	1.0356	1.0601
1912	1.0860	1.0234	1.0171	1.0849	1.1124	1.0368	1.1097
2706	0.9957	0.9991	1.0079	0.9970	1.0052	1.0080	1.0040
2709	0.9877	0.9996	1.0003	***0.9866***	***0.9879***	0.9991	***0.9879***
2713	0.9904	1.0013	1.0047	0.9965	0.9910	1.0035	0.9952
2718	1.0014	1.0010	1.0004	1.0029	1.0026	1.0025	0.9994
2720	1.0174	1.0240	1.0102	1.0399	1.0305	1.0524	1.0673
2721	0.9924	1.0377	1.0031	1.0296	0.9973	1.0435	1.0413
2723	0.9996	1.0007	1.0001	1.0075	1.0025	1.0001	1.0007
2727	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
2732	0.9923	1.0046	1.0011	1.0024	1.0023	1.0077	1.0104
2872	0.9972	0.9996	1.0090	0.9955	1.0087	1.0085	1.0065
3264	0.9972	1.0001	1.0013	0.9981	0.9998	1.0031	1.0001
3287	1.0000	1.0023	1.0009	1.0029	1.0008	1.0043	1.0034
3297	0.9985	1.0011	1.0168	1.0014	1.0140	1.0183	1.0092
3298	1.0096	1.0050	1.0002	1.0064	1.0108	1.0044	1.0054
3396	0.9966	1.0000	1.0023	0.9986	1.0007	1.0023	1.0018
3399	1.0715	1.0000	1.0000	1.0753	1.0751	1.0000	1.0702
3403	1.0124	1.0300	1.0003	1.0516	1.0149	1.0411	1.0596
3405	1.0079	1.0061	1.0000	1.0141	1.0046	1.0130	1.0197
3406	0.9965	1.0045	1.0002	1.0012	0.9978	1.0070	1.0051
3407	0.9937	1.0044	1.0027	1.0006	1.0003	1.0092	1.0067
3644	1.0969	1.0089	1.0169	1.1042	1.1193	1.0225	1.1256
3775	1.0050	***0.9950***	1.0068	1.0041	1.0130	1.0063	1.0112
3776	0.9999	1.0000	1.0118	0.9990	1.0064	1.0111	1.0119
3796	0.9952	0.9984	1.0018	0.9946	1.0019	1.0005	1.0016
3797	0.9972	1.0051	1.0000	0.9996	0.9970	1.0053	0.9972
3803	0.9956	1.0021	1.0001	0.9982	0.9968	1.0026	0.9994
3935	1.0046	0.9989	1.0033	1.0027	1.0056	1.0019	1.0045
3936	1.0042	0.9983	1.0066	1.0021	1.0114	1.0053	1.0099
3938	0.9981	0.9993	1.0089	0.9980	1.0060	1.0090	1.0032
3945	***0.9868***	0.9994	1.0010	0.9923	0.9947	1.0004	0.9933
3954	1.0214	0.9994	1.0023	1.0163	1.0235	1.0020	1.0245
4072	1.0423	1.0078	1.0058	1.0423	1.0548	1.0096	1.0548
4078	1.0095	1.0019	1.0000	1.0132	1.0095	1.0012	1.0133
4158	1.0842	1.0140	1.0008	1.0898	1.0842	1.0113	1.0899
4162	0.9997	1.0000	1.0268	0.9997	1.0272	1.0265	1.0272
6002	1.0028	1.0071	1.0004	1.0220	1.0144	1.0071	1.0414
6085	1.0029	1.0022	1.0134	1.0050	1.0202	1.0165	1.0234
6137	1.0163	1.0015	1.0334	1.0174	1.0696	1.0386	1.0687
6139	1.0000	1.0000	1.0000	1.0578	1.0000	1.0000	1.0550
6193	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
6194	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
6248	0.9992	1.0488	1.0019	1.0563	1.0024	1.0515	1.0580
6264	1.0109	1.0021	1.0025	1.0078	1.0139	1.0040	1.0133
8042	0.9995	1.0000	***0.9999***	0.9982	0.9980	0.9999	0.9983
8066	**1.1418**	1.0104	1.0000	**1.1509**	1.1372	1.0108	1.1500
8069	1.0870	1.0045	1.0013	1.0937	1.1019	1.0139	1.1164
8102	1.0836	1.0000	1.0002	1.0820	1.0837	0.9995	1.0777
8224	1.0640	1.0078	1.0005	1.0919	1.0602	1.0279	1.0952
$\left(\sum_{k=1}^{K}\sum_{t=1}^{T}\hat{\hat{y}}_k^t / \sum_{k=1}^{K}\sum_{t=1}^{T}\hat{y}_k^t\right)$	1.0194	1.0058	1.0039	1.0268	1.0243	1.0116	1.0340

Table A.2
Annual arithmetic means: Y_j^{TP}/Y^{CC}, $j=1,\ldots,3$. $(\sum_{k=1}^{K}\hat{\hat{y}}_k^t/\sum_{k=1}^{K}\hat{y}_k^t)$ for seven combinations of traded bad outputs (1995–2005) (bold = maximum value and bold and italics = minimum value).

Year	SO_2	NO_x	CO_2	SO_2 and NO_x	SO_2 and CO_2	NO_x and CO_2	SO_2, NO_x, and CO_2
1995	1.0195	**1.0093**	1.0038	**1.0325**	1.0233	**1.0161**	1.0389
1996	1.0214	1.0068	1.0037	1.0311	1.0264	1.0129	**1.0399**
1997	1.0204	1.0054	1.0026	1.0310	1.0235	1.0085	1.0342
1998	***1.0146***	1.0073	1.0016	1.0249	***1.0162***	1.0117	1.0300
1999	*1.0157*	1.0054	1.0054	1.0254	1.0216	1.0112	1.0323
2000	1.0192	1.0061	***1.0007***	1.0247	1.0207	***1.0074***	***1.0268***
2001	1.0210	1.0043	1.0052	1.0247	1.0284	1.0100	1.0326
2002	1.0218	1.0034	1.0045	1.0242	1.0270	1.0084	1.0296
2003	**1.0219**	***1.0026***	**1.0065**	***1.0241***	**1.0302**	1.0124	1.0371
2004	1.0191	1.0061	1.0053	1.0260	1.0260	1.0149	1.0380
2005	1.0185	1.0079	1.0036	1.0269	1.0237	1.0143	1.0353
$(\sum_{t=1}^{T}\sum_{k=1}^{K}\hat{\hat{y}}_k^t/\sum_{t=1}^{T}\sum_{k=1}^{K}\hat{y}_k^t)$	1.0194	1.0058	1.0039	1.0268	1.0243	1.0116	1.0340

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