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Tradable permits and unrealized gains from trade☆

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ABSTRACT

With the advent of tradable permit programs for bad outputs (e.g., SO_2 emissions); concerns arose over whether the theoretical gains from trade would be realized. We will employ a methodology that calculates the potential gains accruing to coal-fired electric power plants from implementing a tradable permit program. The magnitude of the potential gains in a plant's kilowatt hour output from a tradable permit program relative to its observed production provides insights into the existence of intertemporal allocative inefficiencies and spatial allocative inefficiencies after the implementation of a tradable permit program.

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1. Introduction

With the advent of tradable permit programs, concerns arose over whether the theoretical gains from trade would be realized. A multitude of factors are sources of the unrealized gains from trade, i.e., the failure of a tradable permit program to equalize marginal abatement costs. As a result, market inefficiencies persist due to a suboptimal allocation of emissions. Because potential efficiency gains were the primary argument for introducing tradable permits, there is great interest in whether tradable permit programs realized the predicted potential gains from trade. Our goal is to address this issue for a sample of coal U.S. fired power plants over the 1995–2005 period. We find relatively low losses of efficiency, i.e., the market has worked well.

Stavins (1995) and Montero (1998) presented early theoretical work on the interaction between transaction costs and tradable permits. Stavins (2007) identified three sources of transaction costs in the tradable permit market: (1) collecting information, (2) bargaining and deciding, and (3) monitoring and enforcement.

Empirical studies include econometric studies (see Gangadharan, 2000) of the Regional Clean Air Incentive Market (RECLAIM) in which transaction cost variables measured information and search costs, and experimental economic approaches (see Cason and Gangadharan, 2003). In addition, Woerdman (2000) and Michaelowa and Jotzo (2005) studied transaction costs associated with the clean development mechanism (CDM). The CDM, which is part of the Kyoto Protocol, allows industrial countries to invest in projects that reduce emissions in developing countries rather than undertaking more costly greenhouse gas emission reducing projects at home.

There have been previous attempts to estimate cost savings from adopting tradable permit strategies instead of employing a command-and-control strategy. Atkinson and Tietenberg (1991) investigate the cost effectiveness of a bubble policy implemented in the St. Louis Air Quality Control Region. They concluded the bilateral, sequential trading occurring under the bubble policy – rather than the modeled multilateral, simultaneous trading — resulted in lower than expected cost savings. Of the four scenarios considered, only one achieved more than 20 percent of the potential cost savings from the bubble program. Newell and Stavins (2003) modeled a second-order approximation of pollution abatement costs around baseline emissions to predict a 51 percent cost savings from employing tradable permits to reduce NO_x emissions in eastern states. Another *ex ante* study, Carlson et al. (2000), estimated potential cost savings from the tradable permit program of 43 percent. However, they found that actual costs were 51 percent (in 1995) and 59 percent (in 1996) higher than under the efficient trading assumption.

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Using data from 87 refineries over 8 quarters, Kerr and Mare (1998) employed an econometric model to estimate the transaction costs of making one trade instead of none that were associated with a tradable permit system for lead emissions. They concluded that these transaction costs resulted in a 10 to 20 percent reduction in cost effectiveness of the tradable permit program.

Here we take a different approach, ours is an *ex post* study in which we use observed data from a sample of coal-fired power plants after trading was introduced, for the period 1995–2005. We then estimate their technical efficiency under three nested models: command-and-control, tradable permits with spatial trading in each year, and finally tradable permits with spatial and intertemporal trading. If our joint production models determine that it is possible for coal-fired plants to attain higher levels of kilowatt hour (kWh) production than the observed kWh production while maintaining observed levels of emissions after the implementation of a tradable permit scheme with no inefficiencies, this will demonstrate the cost of foregone trades (in terms of lower kWh production) under the existing tradable permit system.

We build on a method developed by Brännlund et al. (1998) to gain insights into efficiency losses that might be facing coal-fired power plants. We specify a model of the joint production of good (i.e., kWh) and bad (i.e., SO_2 emissions) outputs. We calculate the maximum kWh production of each plant at its observed level of bad output production, which produces a baseline estimate which we refer to as command-and-control. For the model with spatial trading we calculate maximal kWh for all plants if the observed SO_2 emissions are optimally allocated among the plants in each year. The difference in plant kWh between the first and second scenarios, which is driven by cost heterogeneity in pollution abatement, represents the potential gains from a static spatial tradable permit program.[1] The final step is to calculate maximal kWh for all plants allowing for trading over the 1995–2005 time period.

The remainder of this study is organized in the following manner. Section 2 introduces the model we employ to calculate the maximum gains from establishing a tradable permits system. This provides insights into the extent of inefficiencies due to the suboptimal allocation of bad outputs in limiting the volume of trade in permits and the associated unrealized gains from trade. Section 3 discusses the data and empirical results, and in Section 4 we summarize our findings.[2]

2. Theoretical model

The model presented in this section represents a variation and extension of the Brännlund et al. (1998) specification. While the Brännlund et al. (1998) model assumed a short-run profit maximization, our model measures good output maximization. By choosing good output (kWh) maximization as the firm's objective function, we do not have to invoke prices.

For each individual coal-fired electric power plant, we calculate maximum kWh when command-and-control (i.e., nontradable permits) regulations are imposed on bad output production. The model seeks the maximum good output subject to observed levels of bad output production.

Next, we compute the maximal kWh all firms may achieve given that the emissions of bads can be reallocated among them, keeping the total amount fixed in each year and finally allow for intertemporal trading (i.e., trading with banking and borrowing) as well.[3] A formal specification is introduced through an environmental production technology. We start with a general theoretical underpinning and end up with an environmental production function.

Denote exogenous inputs by $x = (x_1, \ldots, x_N) \in \Re_+^N$ good/desirable outputs by $y = (y_1, \ldots, y_M) \in \Re_+^M$ and bad or undesirable outputs by $b = (b_1, \ldots, b_J) \in \Re_+^J$. In our case, good output is kWh and bad outputs are CO_2, NO_x, and SO_2, all scalars.

The technology is modeled by its output sets

$$P(x) = \{(y, b) : x \text{ can produce} (y, b)\}, x \in \Re_+^N. \tag{1}$$

We assume that $P(x)$ satisfies the standard properties of a technology including $P(0) = \{0\}$, $P(x)$ is compact and inputs are strongly disposable. See Färe and Primont (1995) for a discussion. In addition, we assume that outputs are nulljoint[4] and weakly disposable.[5, 6]

The environmental technology illustrated in Fig. 1 meets the two environmental axioms. First, for any observed (y,b) in $P(x)$ its proportional contraction $(\theta y, \theta b)$ is also feasible, i.e., it belongs to $P(x)$, which is what we mean by weak disposability. Second the only point in common between the good output (y-axis) and the output set $P(x)$ is the origin 0, i.e., b is a byproduct of y, or y is null-joint with b.

Here we only have one good output (kWh), and its maximum is estimated using an Activity Analysis or a Data Envelopment Analysis model. We assume that at each time period $t = 1, \ldots, T$ there are $k = 1, \ldots, K$ observations of inputs $x_k^t = (x_{k1}^t, \ldots, x_{kN}^t)$ good output y_k^t and bad or undesirable outputs $b_k^t = (b_{k1}^t, \ldots, b_{kJ}^t)$ thus the command-and-control kWh production for firm k′ at t can be estimated as

$$\begin{aligned} & R_{k'}^t = \max \ \tilde{y}^t \\ s.t. \quad & \sum_{k=1}^{K} z_k^t y_k^t \geq \tilde{y}^t \\ & \sum_{k=1}^{K} z_k^t b_{kj}^t = b_{k'j}^t, \quad j = 1, \ldots, J \\ & \sum_{k=1}^{K} z_k^t x_{kn}^t \leq x_{k'n}^t \ , \quad n = 1, \ldots, N \\ & z_k^t \geq 0 \ , \quad k = 1, \ldots, K, \quad t = 1, \ldots, T \end{aligned} \tag{2}$$

We impose constant returns to scale (CRS) by assuming nonnegativity on the intensity variables, z_k^t.[7] The good output and inputs are strongly disposable while good and bad outputs are together weakly disposable. In Eq. (2), maximization occurs over z_k^t and $\tilde{y}^t$, while $b_{k'j}^t$ are observed levels of the bad outputs and $x_{k'n}^t$ are observed levels of inputs.

Null jointness at each t is imposed by requiring

$$\sum_{k=1}^{K} b_{kj}^t > 0 \quad j = 1, \ldots, J \tag{3a}$$

and

$$\sum_{j=1}^{J} b_{kj}^t > 0 \quad k = 1, \ldots, K \tag{3b}$$

i.e., each bad output is produced by some firm, at each t. This is confirmed by the data.

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[1] See Färe et al. (2013) for an input-based model that investigates this issue from the perspective of the employment effects of rigidities in tradable permit schemes.

[2] The appendices, data, and GAMS programs are available from the corresponding author upon request.

[3] For the purposes of this study, the terms “firms” and “plants” are used interchangeably.

[4] Shephard and Färe (1974), if $(y, b) \in P(x)$ and $b = 0$ then $y = 0$, this assumption captures the idea that production of the good output generates bad or undesirable byproducts.

[5] Shephard (1970), if $(y, b) \in P(x)$ and $0 \leq \theta \leq 1$ then $(\theta y, \theta b) \in P(x)$.

[6] Our environmental production function model has been criticized by Førsund (2009) and Murty et al. (2012) for not incorporating the materials balance principle.

[7] In order to observe the sensitivity of our results to assumption about the returns to scale, we also specified a non-increasing return to scale technology. This requires adding the following constraint to the LP problem: ($\sum_{k=1}^{K} z_k^t \leq 1$). The results for the non-increasing return to scale technology, which do not differ dramatically from the CRS results presented in this paper, are presented in Appendix A.

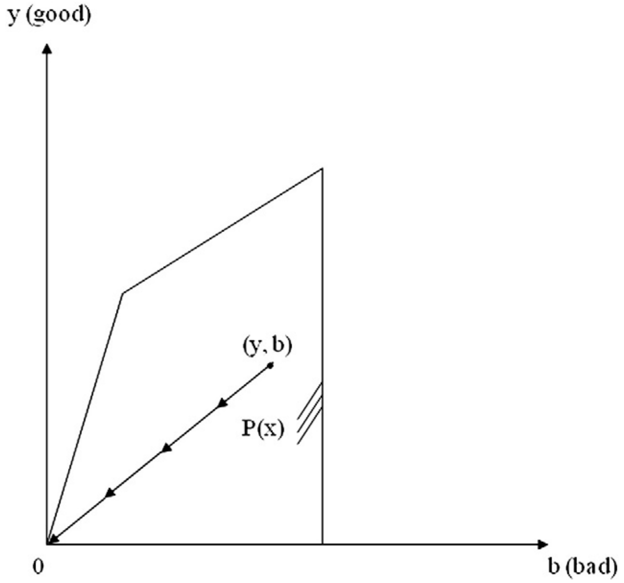

Fig. 1. The environmental technology.

For each k′ and t, the solution to expression (2) gives the maximal good output production firm k′ can obtain when it is only allowed to produce $b_{k'j}^t$ bad output. The industry (maximal) good output at each t is the sum of these maximals.

To estimate the good output at each t when permit trading is allowed for some of the bad outputs, we introduce the aggregate allowed pollution level at t as $B_j^t = \sum_{k=1}^{K} b_{kj}^t$, j = L + 1,…,J which is the observed level of the pollutant subject to tradable permits in period t. The industry maximal good output production, which is the sum of each firm's maximal kWh, is estimated in each period t = 1,…, T as

$$
\begin{array}{lll}
\max \sum_{k=1}^{K} \widetilde{y}_k^t & & \\
\textit{Firm}\ 1 & & \\
s.t.\ \ \sum_{k=1}^{K} z_{k1}^t y_k^t \geq \widetilde{y}_1^t & & \\
\vdots & & \\
\sum_{k=1}^{K} z_{k1}^t b_{kj}^t = b_{1j}^t, & j = 1, \ldots, L & \\
\sum_{k=1}^{K} z_{k1}^t b_{kj}^t = \widetilde{b}_{1j}^t, & j = L+1, \ldots, J & \\
\sum_{k=1}^{K} z_{k1}^t x_{kn}^t \leq x_{1n}^t, & n = 1, \ldots, N & \\
z_k^1 \geq 0, & k = 1, \ldots, K & \\
\textit{Firm}\, K & & \\
\sum_{k=1}^{K} z_{kK}^t y_k^t \geq \widetilde{y}_K^t & & \\
\sum_{k=1}^{K} z_{kK}^t b_{kj}^t = b_{Kj}^t, & j = 1, \ldots, L & \\
\sum_{k=1}^{K} z_{kK}^t b_{kj}^t = \widetilde{b}_{Kj}^t, & j = L+1, \ldots, J & \\
\sum_{k=1}^{K} z_{kK}^t x_{kn}^t \leq x_{Kn}^t, & n = 1, \ldots, N & \\
z_{kK}^t \geq 0, & k = 1, \ldots, K & \\
\text{Aggregate bad output} & & \\
\sum_{k=1}^{K} \widetilde{b}_{kj}^t \leq B_j^t, \quad j = L+1, \ldots, J & &
\end{array}
\tag{4}
$$

In Eq. (4), maximization occurs over z_k^t, $\widetilde{y}_k^t$, and $\widetilde{b}_{kj}^t$. The y_k^t and b_{kj}^t on the left-hand side of the constraints are observed values of the good and bad outputs, while on the right-hand side of the constraints $\widetilde{y}_k^t$ and $\widetilde{b}_{kj}^t$, j = L + 1,…, J are variables (i.e., the bad outputs are tradable). B_j^t, which is the observed level of production of bad output j by the entire sample, must equal or exceed the summation of the firms' b_{kj}^t. Finally, the $x_{k'n}^t$ are observed levels of inputs and b_{kj}^t, j = 1,…, L are observed levels of the bad outputs not subject to tradable permits. The solution (4) yields each firm's maximal good output, $\widetilde{y}_k^t$, for k at t. It also yields the optimal allocation of the bad outputs subject to tradable permits, i.e., $\widetilde{b}_{kj}^t$

The difference between the solutions in Eqs. (2) and (4) summarized over all k = 1, …, K gives us a measure of industry gains from trade for each year. A measure of the *ex post* spatial inefficiency due to the suboptimal allocation of bad outputs – of which transaction costs is one of its components — can be estimated by the solution to Eq. (4) minus the sum of each firm's observed output. We can also compare $\widetilde{b}_{kj}^t$ with observed bad output production to determine whether the elimination of spatial inefficiency would result in firm k′s selling or buying additional permits relative to its observed behavior.

Our last model allows for the reallocation of the bad output not just among firms (k:s) but also over time (t). As a result, the constraint on the quantity of pollutant emitted becomes

$$
B_j = \sum_{t=1}^{T} B_j^t, \quad j = L+1, \ldots, J \tag{5}
$$

In this framework, we maximize the total industry output of all time periods, i.e.,

$$
\begin{array}{lll}
\max \sum_{t=1}^{T} \sum_{k=1}^{K} \widetilde{y}_k^t & & \\
\textit{Firm}\ 1 & & \\
s.t.\ \ \sum_{k=1}^{K} z_{k1}^t y_k^t \geq \widetilde{y}_k^t, & t = 1, \ldots, T & \\
\sum_{k=1}^{K} z_{k1}^t b_{kj}^t = b_{kj}^t, & j = 1, \ldots, L, & t = 1, \ldots, T \\
\sum_{k=1}^{K} z_{k1}^t b_{kj}^t = \widetilde{b}_{kj}^t, & j = L+1, \ldots, J, & t = 1, \ldots, T \\
\sum_{k=1}^{K} z_{k1}^t x_{kn}^t \leq x_{1n}^t, & n = 1, \ldots, N, & t = 1, \ldots, T \\
.z_{k1}^t \geq 0, & k = 1, \ldots, K, & t = 1, \ldots, T \\
. & & \\
. & & \\
\textit{Firm}\ K & & \\
\sum_{k=1}^{K^t} z_{kK}^t y_k^t \geq \widetilde{y}_k^t, & t = 1, \ldots, T & \\
\sum_{k=1}^{K^t} z_{kK}^t b_{kj}^t = b_{kj}^t, & j = 1, \ldots, L, & t = 1, \ldots, T \\
\sum_{k=1}^{K^t} z_{kK}^t b_{kj}^t = \widetilde{b}_{kj}^t, & j = L+1, \ldots, J, & t = 1, \ldots, T \\
\sum_{k=1}^{K^t} z_{kK}^t x_{kn}^t \leq x_{Kn}^t, & n = 1, \ldots, N, & t = 1, \ldots, T \\
z_{kK}^t \geq 0, & k = 1, \ldots, K, & t = 1, \ldots, T \\
\text{Aggregate bad output} & & \\
\sum_{t=1}^{T} \sum_{k=1}^{K} \widetilde{b}_k^t \leq B_j = \sum_{t=1}^{T} B_j^t, & j = L+1, \ldots, J &
\end{array}
\tag{6}
$$

In Eq. (6), maximization occurs over z_k^t, $\widetilde{y}_k^t$, and $\widetilde{b}_k^t$. The y_k^t and b_k^t on the left-hand side of the constraints are observed values of the good and bad outputs, while on the right-hand side of the constraints $\tilde{y}_k^t$ and $\tilde{b}_{kj}^t$ are variables. Eq. (6) allows both banking and borrowing of tradable permits. We may now compare the solutions of Eqs. (4) and (6) to see if the pollution levels have been optimally allocated among firms (k) as well as over time (t). This yields our measure of *ex post* intertemporal inefficiency due to the suboptimal allocation of bad outputs. As with our measure of spatial inefficiency due to the suboptimal allocation of bad outputs, it is possible to determine whether the elimination of intertemporal inefficiency would result in the firm selling or buying additional permits relative to its observed behavior.

Cronshaw and Kruse (1996), which investigated cost minimization strategies for permit trading when banking is permitted, was extended by Rubin (1996) to allow banking and borrowing. Kling and Rubin (1997) extended Rubin (1996) by investigating optimal strategies for banking and borrowing when damage functions are explicitly modeled. In Rubin's model, the regulator minimizes joint-costs by minimizing the sum of discounted emission abatement costs of heterogeneous firms via optimal control theory, while Stevens and Rose (2002) employ a nonlinear programming model. Our model provides an approach to operationalizing the dynamic programming models of Rubin (1996) and Stevens and Rose (2002) within a linear programming framework that permits intertemporal trading without damage functions. However, unlike Rubin (1996) and Stevens and Rose (2002, p. 51, footnote 8), which assume that costs can be assigned to either good output production or pollution abatement, we model the joint production of good and bad outputs to calculate the costs of abating SO_2 emissions.

The magnitude of potential gains from trade reflects the extent of cost heterogeneity (see Carlson et al., 2000; Newell and Stavins, 2003, and Rezdek and Blair, 2005). When intertemporal trades are allowed (Eq. (6)), cost heterogeneity reflects both changes in regulatory stringency and changes in abatement costs associated with technical change.

3. Data and results

The technology modeled in this study consists of one good output, "net electrical generation" in kWh (y) and three bad outputs — CO_2 (b_1), NO_x (b_2), and SO_2 (b_3). The inputs consist of the capital stock (x_1), the number of employees (x_2), and the heat content (in Btu) of the coal, oil, and natural gas consumed at the plant (x_3).[8] 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 and capital data for public power plants.[9] 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 2004–06 data for its electric power plants on-line (http://www.tva.gov/finance/reports/index.htm). While both surveys collect data on the historical cost of plant and equipment, they do not collect data on investment expenditures or depreciation costs. As a result, we assume changes in the cost of plant and equipment reflect net investment (NI). Next, we convert the historical cost data into constant (1973) dollar values using the Handy-Whitman Index (HWI) (Whitman et al., 2006). This is the same procedure employed by Yaisawarng and Douglass Klein (1994, p. 453, footnote 30) and Carlson et al.. (2000, p. 1322). The net constant dollar capital stock (CS) for year n is calculated in the following manner:

$$CS_n = \sum_{t=1}^{n} \frac{NI_t}{HWI_t}. \tag{7}$$

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. Appendix B contains a detailed discussion of the derivation of the capital stock.

The U.S. DOE (Department of Energy) Form EIA-767 survey is the source of information about fuel consumption, and the net generation of electricity. The CO_2, NO_x, and SO_2, emission data are collected by the U.S. EPA Continuous Emissions Monitoring System (CEMS). Our panel consists of 87 coal-fired power plants for 1995 to 2005. While plants may consume coal, oil, or natural gas, in order to model a homogeneous production technology, coal must provide at least 95 percent of the Btu of fuels consumed by each plant.[10] Some plants are excluded due to their consumption of miscellaneous fuels such as: petroleum coke, blast furnace gas, coal-oil mixture, fuel oil #2, methanol, propane, wood and wood waste, refuse, bagasse and other nonwood waste. Although a number of plants consume fuels other than coal, petroleum, and natural gas, these miscellaneous fuels represent very small percentages of fuel consumption (in Btu). In deriving our sample, we exclude a plant when its consumption of miscellaneous fuels represented more than 0.0001 percent of its total consumption of fuel (in Btu). For a plant whose consumption of miscellaneous fuel consumption represents less than 0.0001 percent of its fuel consumption, its consumption of miscellaneous fuels is ignored.[11]

Table 1 reports descriptive statistics for the outputs and inputs for the pooled data consisting of 87 coal-fired electric power plants in 1995 and 2005. Our joint production technology consists of contemporaneous frontiers. Hence, only observations from period t are used to construct the period t reference technology.

We operationalize our model by specifying the models in Eqs. (2), (4), and (6) with CO_2, NO_x, and SO_2 as the bad outputs.[12] Eqs. (4) and (6) assume that SO_2 output can be traded among plants, while NO_x and CO_2 are not tradable.

For the command-and-control model each power plant seeks to maximize its kWh while emitting its observed levels of CO_2, NO_x, and SO_2 emissions. Any increase in electricity production above observed levels represents technical inefficiency. In order to achieve an optimal allocation of bad outputs in a given year, we allow permits for SO_2 to be traded spatially across electric power plants. The foregone potential gains from trade constitute an upper limit on the potential size of transaction costs.

In Table 2 we report the annual results for the command-and-control (CAC) simulation (Eq. (2)), in Table 3 we report when permits are traded spatially — the tradable permit (TP_S) simulation (Eq. (4)), and in Table 4 we report when SO_2 permits are traded spatially and temporally — the tradable permit (TP_ST) simulation (Eq. (6)). In all tables, column (1) represents observed electricity production (in kWh), while

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[8] Because depreciation is not modeled when calculating the capital stock, vintage effects are not captured by the capital stock data used to estimate the production frontiers. Another potential source of error in the results is associated with treating all coal consumed as having the same quality (i.e., sulfur content). Hence, our model does not account for fuel-switching as a strategy to reduce SO_2 emissions.

[9] 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 the cost of plant and equipment, and employment collected by the FERC Form 1 for 1998–2005 and EIA-412 for 1998–2003 are downloaded from their respective websites.

[10] It is possible to expand our sample to include power plants whose primary fuel is oil or natural gas. This can be accomplished in one of two ways. First, the heat input can be modeled as total Btus. The drawback of this approach is it treats all power plants, regardless of fuel, as having identical production technologies. A second approach consists of modeling separate technologies for coal, natural gas, and oil power plants and calculating separate frontiers for each of the three production technologies. This approach would provide more transparent consequences of switching from coal-fired power plants to either natural gas or oil power plants.

[11] Appendix B contains additional information about the data.

[12] In Appendix A, we report the results when we specify the models in Eqs. (2), (4), and (6) with SO_2 as the sole bad output. With only one bad output constraint, the reduced good output due to foregone trades is more than twice as large as the results when modeling three bad outputs.

Table 1
Summary Statistics (inputs and outputs)

	Units	Mean	Sample std. dev.	Maximum	Minimum
Summary statistics (87 coal-fired power plants, 1995)					
Electricity	kWh (in millions)	5520	4797	20,222	167
SO_2	Short tons (in thousands)	38	40	192	2
Capital stock	Dollars (in millions, 1973$)	286	199	863	43
Employees	Workers	207	135	578	32
Heat content of coal	Btu (in billions)	55,254	46,553	193,574	2255
Heat content of oil	Btu (in billions)	106	113	514	0
Heat content of gas	Btu (in billions)	85	273	2083	0
Summary statistics (87 coal-fired power plants, 2005)					
Electricity	kWh (in millions)	6399	5163	22,338	176
SO_2	Short tons (in thousands)	33	33	186	1
Capital stock	Dollars (in millions, 1973$)	325	231	1009	48
Employees	Workers	167	104	468	28
Heat content of coal	Btu (in billions)	64,501	50,229	215,802	2297
Heat content of oil	Btu (in billions)	103	127	738	0.0
Heat content of gas	Btu (in billions)	65	151	911	0.0

column (2) reports SO_2 emissions. Electricity production reported in column (3) of Table 2 is associated with the maximum kWh calculated by Eq. (2), while column (3) of Tables 3 and 4 is associated with the maximum kWh calculated by Eq. (4). Column (4) of Tables 3 and 4 reports SO_2 emissions under the tradable permit systems. Finally column (4) in Table 2 represents the percent increase in electricity production when technical inefficiency is eliminated, while column (5) in Tables 3 and 4 represents the percent increase in electricity production when technical inefficiency and inefficiency due to the suboptimal allocation of bad outputs are eliminated.

The difference in maximum good output production between the CAC simulation and tradable permit simulations (TP_S and TP_ST) constitute the reduced good output associated with regulatory rigidity (i.e., an inefficient allocation of bad output production). For a fixed technology and input vector, less flexible (i.e., less efficient) regulations lead to decreased good output production. Therefore, the maximum levels of good output are highest for the TP_ST simulations and lowest for CAC simulations.

Table 2
Command-and-control (Eq. (2)). (**Bold** = maximum value and *italics* = *minimum* value).

Year	Electricity production in base-case (billion kWh)	SO_2 emissions in base-case (1000 tons)	Electricity production with command-and-control (billion kWh)	Percent increase in electricity with no inefficiency
1995	480.2	3303.5	493.6	2.77
1996	510.4	3624.5	525.9	3.05
1997	526.5	3731.4	543.2	3.18
1998	524.6	3553.2	543.2	**3.55**
1999	528.3	3371.5	544.2	3.01
2000	550.5	3231.9	562.2	2.13
2001	522.2	2924.0	533.7	2.21
2002	530.9	2793.4	545.1	2.66
2003	535.4	2914.3	549.7	2.66
2004	540.1	2804.3	551.5	**2.11**
2005	556.7	2856.9	571.5	2.66
Mean				2.72

Table 3
Tradable permits (spatial trading) (Eq. (4)). (**Bold** = maximum value and *italics* = *minimum* value).

Year	Electricity production in base-case (billion kWh)	SO_2 emissions in base-case (1000 tons)	Electricity production with tradable permits (billion kWh)	SO_2 emissions with tradable permits (1000 tons)	Percent increase in electricity with no inefficiency
1995	480.2	3303.5	501.0	3303.5	4.33
1996	510.4	3624.5	534.2	3624.5	4.67
1997	526.5	3731.4	551.1	3731.4	4.67
1998	524.6	3553.2	549.1	3208.1	4.68
1999	528.3	3371.5	549.8	3336.0	4.07
2000	550.5	3231.9	571.3	3065.8	3.77
2001	522.2	2924.0	542.1	2924.0	3.82
2002	530.9	2793.4	558.6	2793.4	**5.21**
2003	535.4	2914.3	558.9	2914.3	4.39
2004	540.1	2804.3	557.3	2804.3	**3.19**
2005	556.7	2856.9	580.3	2856.9	4.24
Mean					4.27

CAC results are identical to TP_S results only when the observed allocation of bad outputs is optimal. In other words, there is no possibility for the industry to increase its good output by changing the allocation of bad outputs via trades within a given year (spatial). CAC results are identical to TP_ST results only when there is no incentive to change the observed allocation of bad outputs via trades among plants within a given year (spatial) or between years (temporal).

The interpretation of the results depends upon the existing regulatory strategy. If a command-and-control regulatory system exists, Eq. (2) calculates the maximum good output production with the *observed* level of bad outputs for each power plant under the existing command-and-control regulatory structure, the difference between Eqs. (4) and (2) is the *potential* increase in good output production if an efficient spatial tradable permit system is implemented, and the difference between Eqs. (6) and (2) is the *potential* increase in good output production if an efficient spatial and temporal tradable permit system is implemented. If a spatial tradable permit system exists, then Eq. (2) identifies the maximum good output production of each power plant with the *observed* level of bad outputs produced under the tradable permit system, while the difference between Eqs. (4) and (2) is the *foregone* increase in good output production under the existing tradable permit system due to rigidities that limit SO_2 trades, and the difference between Eqs. (6) and (2) is the *potential* increase in good output if regulators implemented an efficient spatial and temporal tradable permit system. If a spatial and

Table 4
Tradable Permits (spatial and temporal trading) (Eq. (6)). (**Bold** = maximum value and **italics** = *minimum* value).

Year	Electricity production in base-case (billion kWh)	SO_2 emissions in base-case (1000 tons)	Electricity production with tradable permits (billion kWh)	SO_2 emissions with tradable permits (1000 tons)	Percent increase in electricity with no inefficiency
1995	480.2	3303.5	501.1	3389.0	4.34
1996	510.4	3624.5	534.3	3654.5	4.68
1997	526.5	3731.4	551.1	3686.6	4.67
1998	524.6	3553.2	549.1	3190.2	4.67
1999	528.3	3371.5	549.7	3186.8	4.05
2000	550.5	3231.9	571.3	3040.0	3.77
2001	522.2	2924.0	542.1	2891.3	3.81
2002	530.9	2793.4	559.7	2922.5	**5.41**
2003	535.4	2914.3	559.4	3032.5	4.48
2004	540.1	2804.3	558.2	3068.8	**3.35**
2005	556.7	2856.9	580.5	3046.8	4.28
Mean					4.32

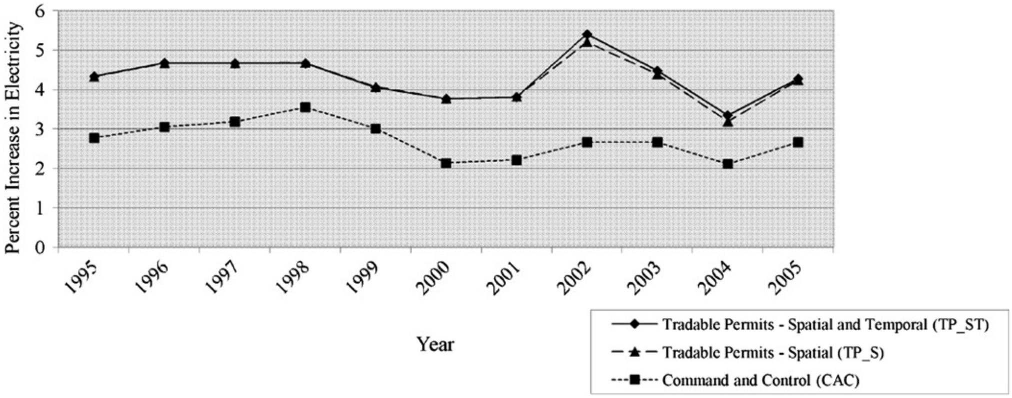

Fig. 2. Percent increase in electricity with elimination of inefficiency.

temporal tradable permit system exists, then Eq. (2) identifies the maximum good output production of each power plant with the *observed* level of bad outputs produced under the existing system of tradable permits, while the difference between Eqs. (4) and (2) is the *foregone* increase in good output production under the existing tradable permit system due to rigidities that limit SO_2 trades spatially, and the difference between Eqs. (6) and (2) is the *foregone* increase in good output under the existing tradable permit system due to rigidities that limit SO_2 trades spatially and temporally.

The results in Table 2 (i.e., the CAC simulation) reveal an average potential increase of 2.72 percent in electricity output (in kWh) during 1995–2005 if technical inefficiency is eliminated. Table 3 (i.e., the TP_S simulation) reveals a potential increase in good output production of 4.27 percent if technical inefficiency and intra-period inefficiency due to the suboptimal allocation of bad outputs are eliminated, and Table 4 (i.e., the TP_ST simulation) reports a potential increase in good output production of 4.32 percent if technical inefficiency, and intra-period and inter-period inefficiency due to the suboptimal allocation of bad outputs are eliminated.[13] The difference in electricity production with no inefficiency between Tables 3, 4 and 2 is the foregone electricity associated with inefficiency due to the suboptimal allocation of bad outputs. Hence, technical inefficiency (the CAC simulation) accounts for more than 60 percent of total foregone good output. Most of the remaining lost good output is due to rigidities in the spatial trading of SO_2 (the difference between the TP_S simulation and CAC simulation), with a small amount of good output foregone due to rigidities in the intertemporal trading of SO_2 permits (the difference between the TP_ST simulation and TP_S simulation).

The inefficiency due to the suboptimal allocation of bad outputs associated with spatial trading, which is found by subtracting the values in the last column of Table 2 (CAC simulation) from the values in the last column of Table 3 (TP_S simulation), ranges from 1.06 percent (in 1999) to 2.55 percent (in 2002). Finally, the inefficiency due to the suboptimal allocation of bad outputs associated with temporal trading, which is found by subtracting the values in the last column of Table 3 (TP_S simulation) from the values in the last column of Table 4 (TP_ST simulation), ranges from −0.02 percent (in 1999) to 0.20 percent (in 2002).

Fig. 2 shows potential annual increases in electricity generation for the three simulations. For all three cases, inefficiency remained stable throughout most of 1995–2005. For the CAC simulation, technical inefficiency attained a minimum of 2.11 percent in 2004, and a maximum of 3.55 percent in 1998. For the TP_S simulation (Table 3), technical inefficiency and inefficiency due to the suboptimal allocation of bad outputs attained a minimum of 3.19 percent in 2004, and a maximum of 5.21 percent in 2002. Finally, technical inefficiency and inefficiency due to the suboptimal allocation of bad outputs attained a minimum of 3.35 percent in 2004, and a maximum of 5.41 percent in 2002 for the TP_ST simulation (Table 4). Of the three cases, the TP_S simulation (Table 3) exhibits the greatest decline in inefficiency (0.62 percent) between 1995–1997 and 2003–2005.

Of the 957 observations (87 plants and 11 years) in our sample, the median increase in electricity production with the TP_S simulation relative to the CAC simulation is 0.11 percent with a mean increase of 1.94 percent. 47 observations report reduced electricity production for the TP_S simulation relative to the CAC simulation, and an additional 350 observations report no difference in electricity production. 45 observations report at least a 10 percent increase in electricity production under TP_S simulation relative to the CAC simulation, 10 observations report at least a 25 percent increase, with the maximum increase being 40.33 percent.

The median increase in electricity production under the TP_ST simulation relative to the TP_S simulation is 0.00 percent with a mean increase of 0.05 percent. While 48 observations report reduced electricity production under the TP_ST simulation relative to the TP_S simulation, 796 report no difference in electricity production, with the maximum increase being 3.23 percent.

The results in Table 3 represent the maximal gains from an efficient spatial tradable permit system, while the results in Table 4 represent the maximum gains from an efficient spatial and temporal tradable permit system. If the models accurately reflect the “real world” these results can be compared with actual behavior (i.e., the level of trades). It is expected that the observed level of permit trading will be less than the least cost level modeled by the joint production model. Hence, the level of trade in the modeled results represents the maximum increase in gains from trade associated with removing rigidities in the market for SO_2 permits.

Fig. 3(a), (b), and (c) are box and whisker representations of the distribution of foregone electricity production associated with inefficiency in 1995, which is the first year of the tradable permit system. In 1995, 30 plants in our sample had at least one unit participating in Phase I. Interestingly, for 1995 the CAC and TP_S simulations found the foregone good output per plant is higher for electric power plants with units

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[13] Because we assume weak disposability (i.e., a regulated technology), there is the possibility that portions of the production frontier may be downward sloping (i.e., it is possible to simultaneously reduce bad outputs and increase the good output). In our results, there are numerous observations associated with the downward sloping portion of the frontier. This can be seen in TP_S results when during 1998–2000 the SO_2 output with trading is less than the observed (i.e., maximum allowable) SO_2 output. In other words, it is possible to maximize good output production without emitting the maximum allowable level of SO_2. In this case, emitting more SO_2 reduces good output production. Färe et al. (forthcoming) and Aparicio et al. (2013), propose an alternative specification of weak disposability that avoids this problem.

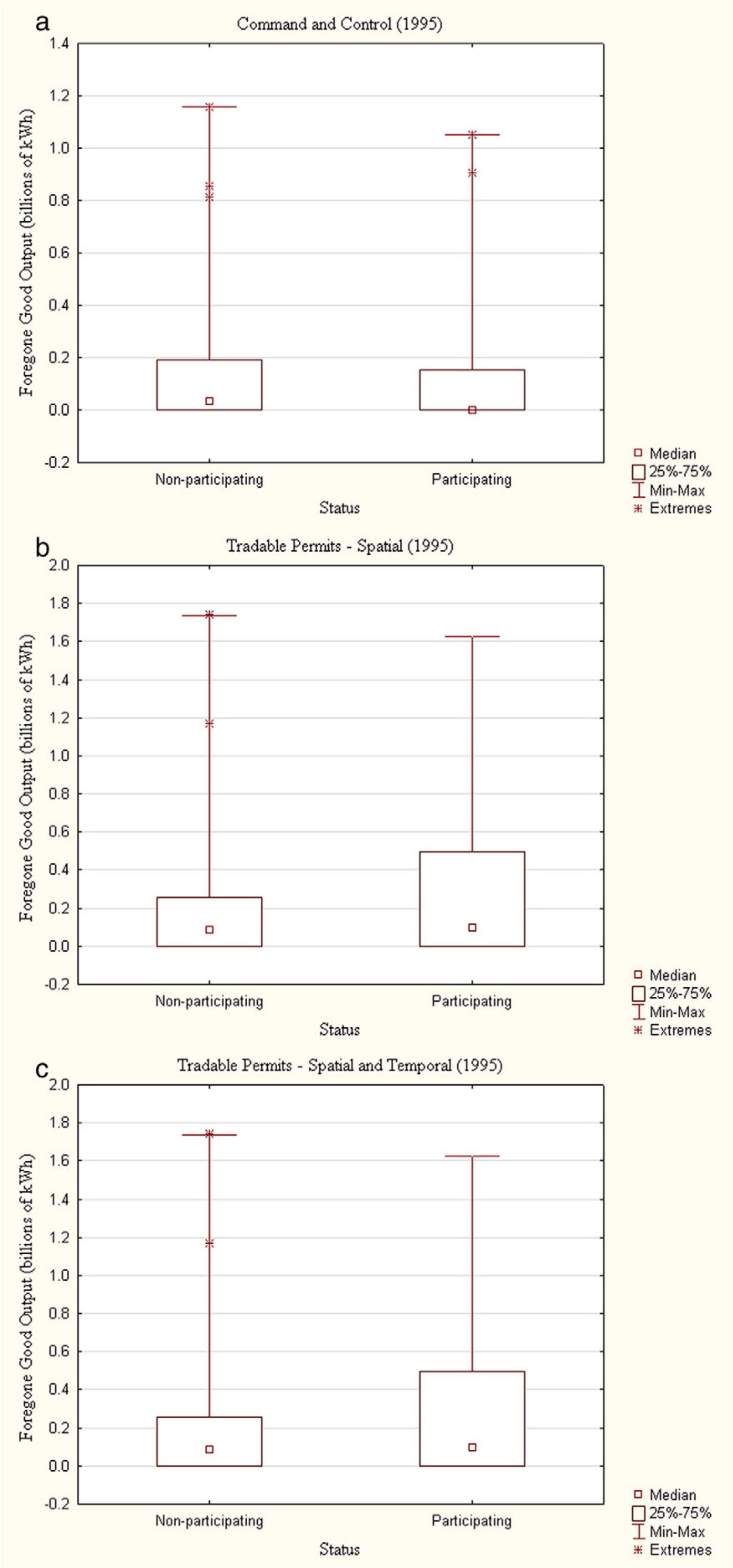

Fig. 3. Box and whisker plots of participating and non-participating plants in phase I of tradable permit system in 1995.

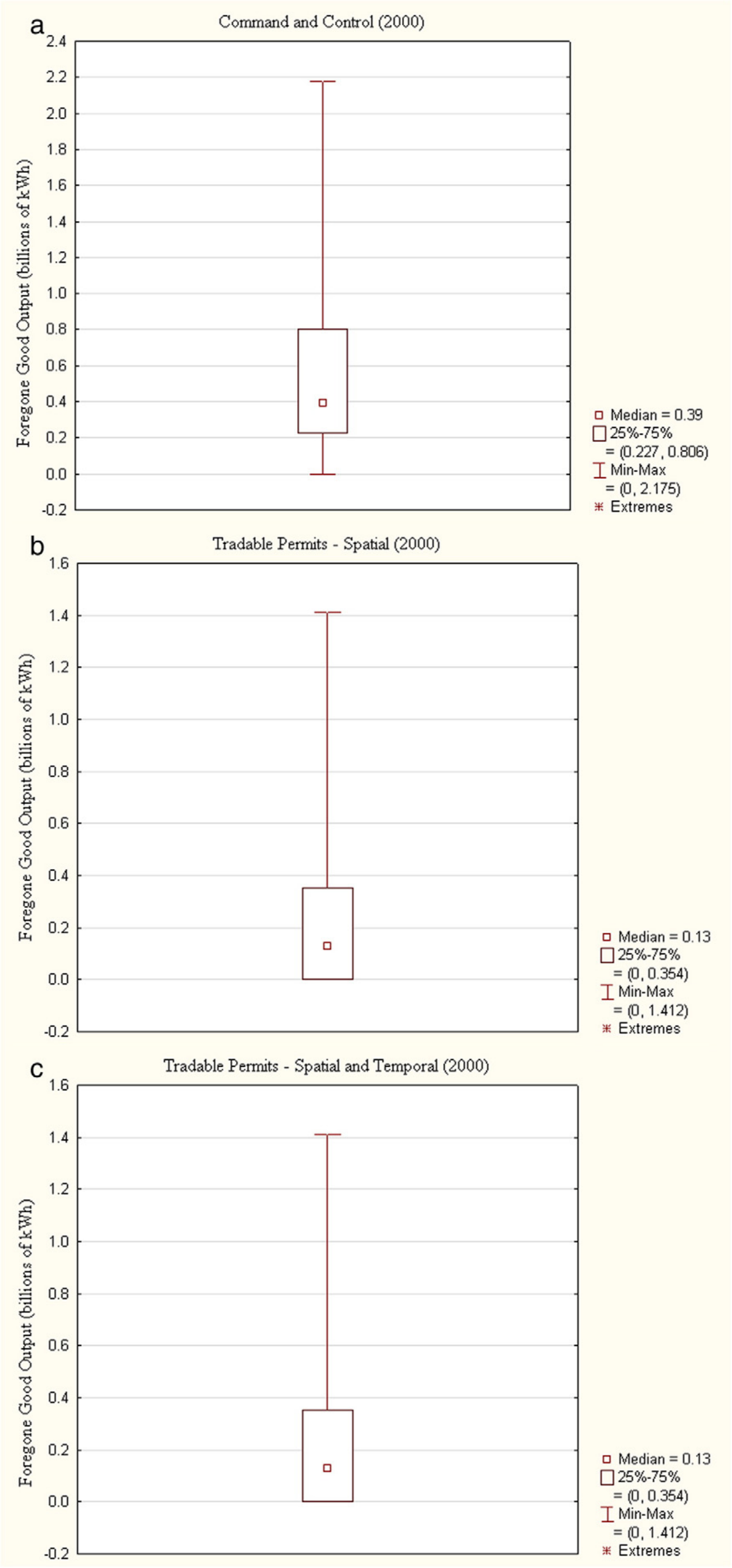

Fig. 4. Box and whisker plots of plants in 2000.

participating in Phase I than for electric power plants that were not participating in Phase I. Fig. 4(a), (b), and (c) are box and whisker representations of the distribution of foregone electricity production associated with inefficiency in 2000, which is the first year of Phase II of the tradable permit system. With the advent of Phase II, all plants in our sample became part of the tradable permit system.

4. Conclusions

After championing market-based systems to minimize the costs associated with attaining targeted reductions in bad output production, economists are naturally concerned about the extent to which rigidities in trading SO_2 permits constitute a barrier to attaining these cost reductions relative to command-and-control regulatory schemes. We have set forth an approach to establish an upper limit on the extent to which transaction costs reduce some of the theoretical gains from trade. In the process we demonstrate how to implement applications of theoretical programming models (e.g., Rubin, 1996; Stevens and Rose, 2002).

By increasing the efficiency of a tradable permit system, we demonstrated that it is possible to increase good output production with the same level of bad outputs and inputs. The failure to execute all beneficial trades results in lower good output production for a given input vector and bad output vector. Hence, it is not surprising that the model with the least mobility of bad output production – the command-and-control model — produces the lowest level of good output. Because inefficiency due to the suboptimal allocation of bad outputs for spatial permit trading and spatial and temporal permit trading was detected, transaction costs may be present; however, its magnitude appears to be relatively 'small.'[14]

Unlike Rubin (1996) and Stevens and Rose (2002), we are able to implement intertemporal trading assuming a zero discount rate because we are using kWh instead of dollars in our objective function. Hence, a potential extension of our intertemporal model would be to have plants maximize revenue instead of kWh which would allow the imposition of exogenous discount rates. This would allow us to investigate whether a plant banks or borrows permits based on the association (see Stevens and Rose, 2002) between the difference in the rate of growth of mitigation costs and technical change relative to the discount rate. An alternative approach would involve modeling discount rates endogenously within a non-linear programming problem. This approach would yield the discount rate that maximizes the discounted revenue stream to each electric power plant.

One possible extension of the model involves adding non-coal power plants to our sample. This would necessitate specifying separate production technologies for coal-fired and non-coal-fired power plants. This would permit utilities to fuel-switch by allowing electricity generated by non-coal-fired plants to substitute for electricity generated by coal-fired power plants.

Our model also assumes homogeneous sulfur content for the coal and oil consumed by the power plants. Incorporating the effect of switching from high-sulfur to low-sulfur coal will require adding the appropriate fuel quality constraints to the specification of the production technology.

Our models assume total factor immobility. Hence, another possible extension of this model involves allowing for factor mobility among power plants (see Brännlund et al., 1998). While capital (i.e., generating capacity or FGD equipment) is immobile, labor and fuel can be shifted among power plants. This would be introduced via a constraint similar to the bad output constraint for the tradable permit case. Allowing some factor mobility makes our model less of a partial equilibrium model.

An additional extension involves modifying trades permitted. For example, we could restrict intertemporal trading by disallowing borrowing by electric power plants. This would be comparable to the system implemented in the United States under the 1990 Clean Air Act Amendments. Finally, we could model alternative strategies for allocating the initial distribution of permits (see Rehdanz and Tol, 2009).

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2013.07.015.

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[14] See Ellerman and Montero (2007) an *ex post* analysis of whether the observed level of banking is optimal.