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Interfaces with Other Disciplines

Technical change and pollution abatement costs[☆]

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ABSTRACT

There is continuing interest in the trend of costs associated with pollution abatement activities. We specify an environmental production technology to model the joint production of good and bad outputs. The joint production model calculates pollution abatement costs and identifies changes in these costs associated with: (1) technical change, (2) input changes, and (3) changes in bad output production. Estimates of the relative importance of each factor are estimated using data from 1995 to 2005 for a sample of coal-fired power plants in the United States. Finally, we discuss the potential usefulness of the decomposition model for identifying discrepancies between ex ante and ex post pollution abatement costs that are linked to the underlying joint production model.

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1. Introduction

In recent decades the United States has enjoyed considerable success in reducing emissions of pollutants – the undesirable byproducts of production and consumption activities. One industry that has attracted considerable interest is the electric power industry. Table 1 lists the net generation of electricity from coal combustion, SO_2 emissions from coal combustion, and SO_2 emissions (in thousands of short tons) per billion kilowatthours (kWh). By 1995, SO_2 emissions per kWh were only 72 percent of the 1989 ratio. With the advent of Phase I of the SO_2 tradable permit program in 1995, the generation of electricity by coal increased by 18 percent between 1995 and 2005, while SO_2 emissions declined by 14 percent. As a result, SO_2 emissions per kWh declined by an additional 27 percent between 1995 and 2005.

If increasing marginal abatement costs characterize pollution abatement, the substantial decline in the SO_2 emission-intensity of electricity production should yield a corresponding increase in pollution abatement costs (PAC).[1] Once a society decides to implement policies to reduce its undesirable byproducts, there are four strategies available to reduce its production of bad outputs: (1) reduce good output production (moving down a given Leontief production ray which results in a proportional decline in good and bad output production), (2) input quality changes (i.e., the most commonly observed is fuel switching), (3) end of pipe (EOP) abatement technologies, and (4) change in process (CIP) abatement technologies. One strategy for measuring the cost of reducing bad outputs is surveying producers about the costs of inputs assigned to pollution abatement. Despite their widespread popularity, these surveys have a major weakness associated with efforts of producers to estimate the abatement costs associated with change-in-process abatement techniques. In this paper, we employ an alternative strategy to address the cost and productivity consequences of reducing the undesirable byproducts of production – modeling the joint production of good and bad output production.

The definition of PAC specified in this paper is not a narrower definition than the cost of inputs approach. Instead, it represents an alternative perspective to assigned input models that require information on the cost of inputs assigned to pollution abatement. In fact, when CGE models are used to assess the cost of regulations to reduce CO_2 emissions, they employ a special case of the joint production model.

This paper will calculate changes in opportunity costs – the foregone production of electricity – of reducing SO_2 emissions and the

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[1] This is expected because for a given technology and input vector, a reduction in bad output per unit of good output (i.e., increased emission-intensity) will yield increased pollution abatement costs (i.e., increased levels of foregone good output production).

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Table 1
Trends in SO_2 emissions from coal consumption at electric power plants.

Year	Net generation from coal (billion kWh)	SO_2 emissions from coal (thousand short tons)	SO_2 (1000 short tons)/billion kWh	SO_2/kWh relative to SO_2/kWh in 1989
1989	1554	13,815	8.9	1.00
1990	1560	13,576	8.7	0.98
1991	1552	13,590	8.8	0.99
1992	1577	13,375	8.5	0.95
1993	1642	13,133	8.0	0.90
1994	1640	12,695	7.7	0.87
1995	1658	10,573	6.4	0.72
1996	1743	11,129	6.4	0.72
1997	1793	11,515	6.4	0.72
1998	1823	11,373	6.2	0.70
1999	1832	10,843	5.9	0.67
2000	1911	10,140	5.3	0.60
2001	1852	9281	5.0	0.56
2002	1881	9106	4.8	0.54
2003	1916	9255	4.8	0.54
2004	1921	8991	4.7	0.53
2005	1956	9071	4.6	0.52

Source: U.S. Department of Energy (2011, pp. 238 and 330).

relative importance of the factors associated with changes in PAC. After specifying unregulated and regulated production technologies in which good (net electricity generation) and bad (e.g., SO_2 emissions) outputs are jointly produced, we will demonstrate that changes in PAC between period t and period $t+1$ are associated with three factors: (1) changes in inputs, (2) changes in bad output production, and (3) technical change.[2]

A decrease (increase) in bad output production is associated with an increase (decrease) in PAC, while an increase (decrease) in inputs is associated with an increase (decrease) in PAC. In addition to the direct effect of reduced bad output production, the increased PAC associated with reduced bad output production can also indirectly affect PAC. For example, an increase in the intensity of abatement activities can affect the quantity of inputs employed by a plant as inputs are shifted among plants within an industry and among other industries. Hence, increased abatement activities can be associated with a decline in PAC as a result of a decrease in the quantity of inputs employed by a plant or industry. While it is possible to expand the specification of our model to include factor mobility among plants in an industry, we do not incorporate these indirect effects on PAC into our paper.

Whether technical change is associated with an increase or decrease in PAC, depends on the relative technical change associated with the unregulated and regulated technologies. If unregulated technical change is higher (lower) than regulated technical change, PAC will increase (decrease). One explanation for declining PAC is that as a society imposes environmental regulations, R&D effort is expended on developing processes capable of producing fewer bad outputs per unit of good output (see DeBoo, 1993). As R&D expenditures associated with processes that produce relatively large quantities of bad outputs per unit of good output are reduced, there is a slowdown in technical progress associated with those processes. Eventually, this regulatory induced technical change results in the less bad output intensive processes being capable of producing as much of the good output as the original free disposability (or less-regulated) technology. When this occurs, the opportunity costs of pollution abatement (i.e., good output production reduced as a result of pollution abatement) cease to exist. In summation, while regulations provide incentives for the regulated technology to innovate, no comparable incentives exist for innovation in the unregulated technology. As a result, we anticipate the regulated technology will exhibit higher rates of technical progress than the unregulated technology.

Using data for the twenty two-digit SIC manufacturing industries in the United States for 1970 to 1990, Pasurka (2001) found evidence supporting DeBoo's (1993) hypothesis that the opportunity cost of meeting a hypothetical constraint on emissions declined as a result of the technical change induced by environmental regulations. However, technical change is only one of several factors associated with changes in PAC. This study extends Pasurka (2001) by specifying a formal model that accounts for the association between three factors and changes in PAC.

In this paper we specify a production technology where good and bad outputs are produced jointly. From the original work of Färe and Grosskopf (1983) and Färe, Grosskopf, Lovell, and Pasurka (1989) that focused on the opportunity cost of pollution abatement, applications of the joint production framework – and discussions about the validity of its assumptions – have increased dramatically in recent years. Liu, Meng, Li, and Zhang (2010) and Sahoo, Luptacik, and Mahlberg (2011) discussed different approaches developed by researchers for modeling good and bad outputs when the bad output is regulated. For example, Seiford and Zhu (2002, 2005) and Färe and Grosskopf (2004) discussed different strategies for modeling bad outputs. While Färe and Grosskopf specified a production technology that imposes weak disposability and null jointness,[3] Seiford and Zhu maintained the standard DEA model for good outputs by transforming the values of bad outputs. The transformation was accomplished by multiplying bad output values by "-1" and then adding a translation vector value to each observation to ensure that all transformed bad output values are non-negative. Because the strategy adopted by Seiford and Zhu is not translation invariant, this model may generate different efficiency values than the Färe and Grosskopf models. Leleu (2013) proposed a linearization of the Färe, Grosskopf, and Pasurka (1986) non-linear specification of the joint production model with variable returns to scale. Leleu also proposed a solution to the problem of joint production models generating counter-intuitive signs for the shadow prices of bad outputs. An alternate solution to this problem was recently proposed by Färe, Grosskopf, and Pasurka (2014).

[2] The regulated technology depicts the case when a producer is interested in reducing bad output production. From the perspective of the joint production model, the motivation of the producer is irrelevant. Whether the reduction in the bad output is due to a voluntary action (i.e., a response to consumers wishing to purchase "green" electricity) or involuntary action (i.e., a government imposed regulation), the regulated technology is the relevant technology. The unregulated technology is the relevant technology when the producer is allowed to ignore the bad outputs it produces.

[3] Another variation can be found in Ball, Färe, Grosskopf, and Zaim (2005) which specified a non-parametric cost function with good outputs and bad outputs that are weakly disposable and null-joint.

In addition to investigating the assumptions that underpin joint production models, other researchers have searched for new applications. For example, Hwang, Chen, Chen, Lee, and Shen (2013) extended the joint production model away from comparing the relative efficiency of producers to assessing the relative efficiency of products (i.e., different automobile models that possess both good and bad characteristics).

The remainder of this study is organized in the following manner. In Section 2, PAC is defined in terms of an environmental production function and its associated specification as a series of LP programs is provided. Section 3 specifies the change in PAC and how to decompose PAC changes into its components. In Section 4, the data and results are presented, and Section 5 summarizes this study, examines the implications of the empirical results of this study, and discusses future avenues of research.

2. Pollution abatement costs with an environmental production function

In this section we formulate the environmental technology. This technology incorporates weak disposability of outputs and nulljointness.[4] The latter concept tells us that producing good outputs is accompanied by the production of bads.[5] After we show that our environmental production function can be "reduced" to a traditional production function, we identify the special conditions the environmental production function must satisfy. This is useful since most previous studies investigated the relationship between pollution abatement activities and changes in good output production (see Pasurka, 2008).

Before proceeding, some notation must be introduced. Inputs are denoted by $\mathbf{x} = (x_1, \ldots, x_N) \in \Re^N_+$, good outputs by $\mathbf{y} = (y_1, \ldots, y_M) \in \Re^M_+$ and bad or undesirable outputs by $\mathbf{b} = (b_1, \ldots, b_J) \in \Re^J_+$. The bad outputs consist of the undesirable byproducts (e.g., SO_2) produced by a coal-fired electric power plant when it produces electricity.[6]

We employ output sets to model the general environmental technology, i.e.,

$$P(\mathbf{x}) = \{(\mathbf{y}, \mathbf{b}) : \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{b})\},\ \mathbf{x} \in \Re^N_+$$

In words, for each input vector $\mathbf{x}$, the output set $P(\mathbf{x})$ consists of the combinations of good and bad outputs $(\mathbf{y}, \mathbf{b})$ that can be produced by that vector. We model the idea that it is "costly" to reduce the bad outputs by imposing the assumption that good and bad outputs $(\mathbf{y}, \mathbf{b})$ are together weakly disposable.[7] By "costly" we understand that one must give up good outputs if one wants to reduce the bad outputs, either directly by reducing production or indirectly by redirecting some of the given input vector to abatement activities.[8]

This environmental technology is required to satisfy the following standard axioms:

P.1. $\{0\} \in P(\mathbf{x})$ for all $\mathbf{x} \in \Re^N_+$
P.2. $P(\mathbf{x})$ is compact $\mathbf{x} \in \Re^N_+$
P.3. $P(\mathbf{x}) \subseteq P(\mathbf{x}')$ if $\mathbf{x}' \geq \mathbf{x}$

These standard axioms tell us that inactivity is always possible (P.1.), that finite inputs can only produce finite outputs (P.2.) and that inputs are freely disposable (P.3.).

In order to specify the environmental technology, the technology also meets two environmental axioms, namely weak disposability of outputs:

P.4.W. $(\mathbf{y}, \mathbf{b}) \in P(\mathbf{x})$ and $0 \leq \theta \leq 1$ imply $(\theta\mathbf{y}, \theta\mathbf{b}) \in P(\mathbf{x})$

i.e., if $\mathbf{x}$ can produce outputs $(\mathbf{y}, \mathbf{b})$, then it is feasible to reduce these outputs proportionally. This axiom should be contrasted with the usual strong disposability condition:

P.4.S. $(\mathbf{y},\mathbf{b}) \in P(\mathbf{x})$ and $(\mathbf{y}',\mathbf{b}') \leq (\mathbf{y},\mathbf{b})$ imply $(\mathbf{y}',\mathbf{b}') \in P(\mathbf{x})$,

which allows for non-proportional reduction in both good and bad outputs. In principle, with free disposability one can costlessly dispose of outputs.[9] While this may make sense for the good output, it does not for the bads since we assume that firms face environmental regulations. If these regulations did not exist (or are not binding) then bads would be freely disposable.[10] This can be used to model the (counterfactual) unregulated environmental technology.[11]

The second environmental axiom is nulljointness or the byproduct axiom.

P.5. $(\mathbf{y},\mathbf{b}) \in P(\mathbf{x})$ and $\mathbf{b} = 0$ imply $\mathbf{y} = 0$

Here the bad outputs $\mathbf{b} = (b_1, \ldots, b_J)$ are byproducts of the good outputs $\mathbf{y} = (y_1, \ldots, y_M)$. This axiom tells us that if we produce good outputs then some bad outputs are also produced. In a nutshell, "there is no fire without smoke."

We assume, for simplicity that the good outputs are freely disposable, i.e.,

P.6. $(\mathbf{y},\mathbf{b}) \in P(\mathbf{x})$ and $y' \leq \mathbf{y}$ imply $(\mathbf{y}',\mathbf{b}) \in P(\mathbf{x})$

In summary, the environmental technology specified in this study assumes good outputs are freely disposable, and good and bad outputs are jointly weakly disposable. We may illustrate the environmental technology using an output set $P(\mathbf{x})$.

The environmental technology illustrated in Fig. 1, satisfies the two environmental axioms introduced above. First, for any observed $(\mathbf{y},\mathbf{b})$ in $P(\mathbf{x})$ its proportional contraction $(\theta\mathbf{y}, \theta b)$ is also feasible, i.e., it belongs to $P(\mathbf{x})$. Second the only point in common between the good output (y-axis) and the output set $P(\mathbf{x})$ is the origin 0, i.e., positive $\mathbf{y}$ cannot be produced without $\mathbf{b}$, which is thus a byproduct of $\mathbf{y}$, or $\mathbf{y}$ is null-joint with $\mathbf{b}$.

In order to formulate the environmental technology as a traditional production function, we need to assume that only a single good output is produced. Assuming $\mathbf{y} \in \Re_+$, we may define the environmental production function as[12]

$$F(\mathbf{x}; \mathbf{b}) = \max\{\mathbf{y} : (\mathbf{y}, \mathbf{b}) P(\mathbf{x})\} \tag{1}$$

[4] Førsund (2009) and Murty, Russell, and Levkoff (2012) undertook theoretical and empirical investigations of the failure of joint production models to account for material balance conditions.

[5] Baumgärtner, Dyckhoff, Fabera, Proops, and Schiller (2001) discuss the relationship between joint production and thermodynamics.

[6] While the data used in this paper consist of electric power generation and SO_2 emissions, the model is applicable to any production technology that produces good and bad outputs.

[7] Weak disposability is the feasibility of proportional reduction in all good and bad outputs. Shephard (1970) introduced this concept.

[8] Carbon capture and storage (CCS), which captures carbon from flue gases, consumes some of the electricity produced by the power plant. As a result, pollution abatement reduces the amount of electricity that can be delivered by the plant to the electrical grid.

[9] Free disposability simply means that the producer can freely dispose of – or ignore – the bad outputs it generates (i.e., the producer can dump the bad outputs without costs in the absence of regulation). While the bads may be jointly produced, with no regulations the unregulated frontier only indicates that the bad output can be disposed of with no cost to the producer. Hence, free disposability does not claim to overturn the laws of thermodynamics.

[10] Because the good and bad outputs are jointly produced, it follows that weak disposability exists. Indeed, weak disposability holds even under strong or free disposability.

[11] The "unregulated" frontier was a term adopted in order to provide readers not familiar with the concepts of weak and free disposability some intuition into what the production frontiers depict. In reality, the existence of regulations on industries in the United States means there is no observable "unregulated" frontier. Instead, the "unregulated" frontier shows the maximum good output production for the least regulated production processes for which data are available. Because the unregulated frontier yields the maximum potential good output production for a given input vector and technology, it constitutes the baseline technology for the purpose of calculating the opportunity cost (i.e., foregone good output production) of pollution abatement.

[12] This definition was introduced by Russell (1998) for good output production.

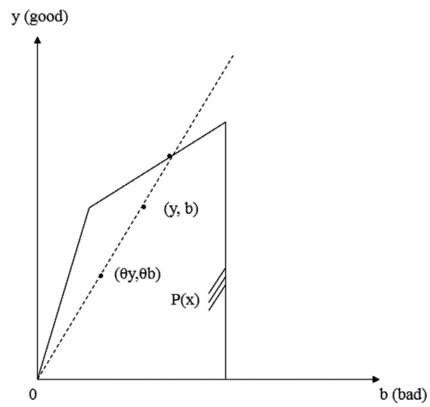

Fig. 1. The environmental technology.

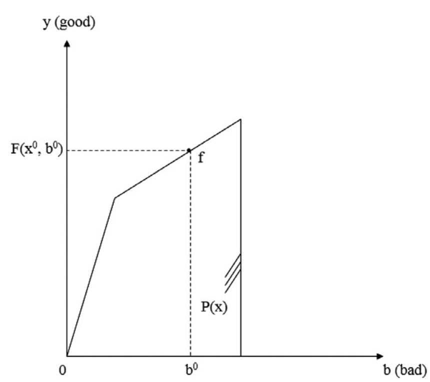

Fig. 2. The environmental production function.

Since $P(\mathbf{x})$ is a non-empty, compact set (P.1 and P.2), the environmental production function, $F(\mathbf{x};\ \mathbf{b})$, exists. Moreover, it is nondecreasing in $\mathbf{x}$ due to P.3. The two environmental axioms imply that $F(\mathbf{x};\ \mathbf{b})$ meets the following conditions

$$\text{if } \mathbf{y} \le F(\mathbf{x};\ \mathbf{b}) \text{ and } 0 \le \theta \le 1, \text{ then } \theta\,\mathbf{y} \le F(\mathbf{x};\ \theta\mathbf{b}) \tag{2}$$

and

$$F(\mathbf{x};\ 0) = 0. \tag{3}$$

The last condition tells us that $\mathbf{b}$ is essential for the production of good outputs. This follows from P.5, our null-jointness assumption, since if $\mathbf{y} = F(\mathbf{x};\ \mathbf{b})$ and $\mathbf{b} = 0$, then $\mathbf{y} = 0$. In modeling the environmental production function one needs to remember that $\mathbf{b}$ is an output – *it is not an input.*[13]

To illustrate how the environmental production function is defined, let x^0 and b^0 be given, then $F(x^0;\ b^0)$ is the maximal feasible production of the good output, see point f in Fig. 2. If we assume that the good output is freely disposable, then if $\mathbf{y} \le F(\mathbf{x};\ \mathbf{b})$, $\mathbf{y}$ is feasible. Under this condition, we may recover the output set by defining:

$$P(\mathbf{x}) = \{(\mathbf{y},\ \mathbf{b}) : \mathbf{y} \le F(\mathbf{x};\ \mathbf{b})\} \tag{4}$$

Thus the environmental production function is a complete characterization of the single output environmental technology.[14]

To operationalize one may adopt a parametric formulation of the production function or use activity analysis. Here we illustrate the latter. Assume that there are $k = 1, \ldots, K$ observations of inputs and outputs, i.e., (y^k, b^k, x^k) $k = 1, \ldots, K$ are known. We may then write the regulated production function (i.e., a model with restrictions on bad output production) for observation k' as:

$$\begin{aligned} F(x^{k'};\ b^{k'}) = \max \quad & \sum_{k=1}^{K} z_k y_k \\ \text{s.t.} \quad & \sum_{k=1}^{K} z_k b_{kj} \le b_{k'j}, \quad j = 1, \ldots, J, \\ & \sum_{k=1}^{K} z_k x_{kn} \le x_{k'n}, \quad n = 1, \ldots, N, \\ & z_k \ge 0, \quad k = 1, \ldots, K, \end{aligned} \tag{5}$$

where $b_{k'j}$ is the observed production of bad output j by the k' producer and $x_{k'n}$ is the observed use of input n by the k' producer. The z_k ($k = 1, \ldots, K$) are the intensity variables, which are weights assigned to each observation when constructing the production set (i.e., the production frontier). Since only a non-negative constraint is imposed on the z_k, constant returns to scale (CRS) are assumed. 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 with the original specification of weak disposability, we decided to maintain a relatively simple framework for this initial effort to decompose changes in pollution abetment costs.[15]

The objective function represents the maximum amount of the good output that can be produced. The best-practice frontier is constructed from observed processes. The constraint in (5) on the bad outputs (b_{kj}, $j = 1, \ldots, J$), allows for weak disposability, i.e., the good and bad outputs can be scaled down jointly to zero, but one cannot freely dispose of the bads. The standard definition of weak disposability is modeled in the production function via a strict equality constraint for the bad outputs. Here, we introduce a modified weak disposability assumption that imposes a less than or equal constraint on the bad output. This specification of the bad output constraint, which was introduced in Färe et al. (2014), avoids infeasibilities when we compare efficiency across different periods.[16] Another advantage of this specification of the bad output constraint is that it allows us to avoid the case when more of the good output can be produced by producing less of the bad output. This eliminates the possibility of a downward sloping portion of the frontier, which ensures the bad output has a nonpositive shadow price (i.e., it is not possible to simultaneously reduce bad output production and increase good output production). The second constraint of the LP problem represents the input constraints. There is a separate constraint for each of the N inputs.

We assume

$$\begin{aligned} &\text{(a)} \sum_{j=1}^{J} b_{kj} > 0 \quad k = 1, \ldots, K \\ &\text{(b)} \sum_{k=1}^{K} b_{kj} > 0 \quad j = 1, \ldots, J \end{aligned} \tag{6}$$

i.e., each row and column has at least one positive element. This assumption imposes nulljointness (or essentiality), which we can see by choosing $b_{k'j} = 0$ for $j = 1, \ldots, J$ in (5). In this case, all $z_k = 0$ and hence $F(x^{k'}, 0) = 0$, i.e., there is no output. We leave it to the reader to show that the production function (5) satisfies (1) and that it exhibits constant returns to scale, here meaning that

$$F(\lambda\mathbf{x};\ \mathbf{b}) = \lambda F(\mathbf{x};\ \lambda\mathbf{b}),\ \lambda > 0 \tag{7}$$

or equivalently

$$P(\lambda\mathbf{x}) = \lambda P(\mathbf{x}),\ \lambda > 0 \tag{8}$$

[13] Cropper and Oates (1992, p. 678) provide an example of a theoretical model that treats bad outputs as inputs, which contradicts axiom P.2.

[14] Färe, Grosskopf, and Pasurka (2007a) demonstrate that environmental production functions are special cases of environmental directional distance functions.

[15] Another option is specifying a non-increasing return to scale technology. This requires adding the following constraint to the LP problem: $\sum_{K=1}^{K} z_k \le 1$.

[16] In principle, the inequality could yield unbounded output sets. This could 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, Pastor, and Zofio (2013).

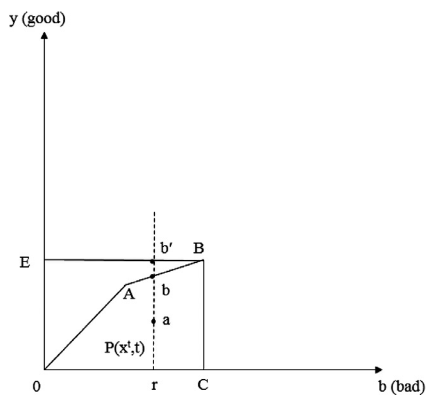

Fig. 3. Production frontiers in period *t*.

To evaluate and estimate the cost of pollution abatement we now introduce the unregulated technology. If society refrains from regulating the environment, then each decision making unit (DMU) would be able to freely dispose of its undesirable byproducts. This situation can be modeled by assuming *all* outputs, good as well as bad are freely disposable.

In the case of a single good output we may compare the value of our environmental production function when the bad output is regulated and unregulated. The unregulated formulation (i.e., a model without restrictions on bad output production) of (5) is:[17]

$$\begin{aligned} G(x^{k'}) = \max \quad & \sum_{k=1}^{K} z_k y_k \\ \text{s.t.} \quad & \sum_{k=1}^{K} z_k x_{kn} \le x_{k'n}, \quad n = 1, \ldots, N, \\ & z_k \ge 0, \quad k = 1, \ldots, K, \end{aligned} \tag{9}$$

The difference between (5) and (9) is the elimination of the constraints in (9) on the bad outputs ($b_{kj}, j = 1, \ldots, J$).[18] The removal of this constraint imposes free disposability on the bad output.

We use (5) and (9) to define pollution abatement costs (PAC) as:

$$\text{PAC} = G\left(x^{k'}\right)/F\left(x^{k'}; b^{k'}\right) \tag{10}$$

which is the ratio of the maximum feasible good output production of the unregulated and regulated technologies for a given level of abatement activity. It measures the reduced good output production – the opportunity cost of pollution abatement – when the bad output is not freely disposable. Hence, PAC is unity if there is no reduced good output production associated with pollution abatement activities, and is greater than unity when pollution abatement activities are associated with reduced good output production.

In Fig. 3, the regulated (0ABC) and unregulated (EB) frontiers represent combinations of good and bad outputs that can be produced by the period t input vector and technology.[19],[20] Because point *a* – the good and bad output production in period *t* – is technically inefficient, it is projected to the regulated and unregulated frontiers.[21] Technical inefficiency in the regulated environment is represented by the vertical distance between an observation and the regulated frontier (rb/ra), where r is the observed bad output production in period t. A decrease in technical inefficiency increases good output production, while increased inefficiency reduces good output production. If we define PAC as the ratio of good output production when the bad output is unregulated (i.e., freely disposable) to observed good output production (i.e., rb'/ra), then PAC includes the reduced good output production associated with inefficiency.[22] Because we define PAC as the ratio of maximum good output production when the bad output is unregulated to its maximum regulated production, the decline in good output production associated with technical inefficiency is excluded. Hence, PAC is defined as (rb'/rb). This index is the increase in good output production that occurs when the DMU can freely dispose of the bad output. In the next section, we extend the single-period model to the two-period case and examine its relationship with changes in PAC.

3. Changes in PAC

In order to formally define the cost of abatement activities, in the previous section we specified technologies that describe the production of *one* good output when the bad output is freely disposable – the unregulated technology, and when the bad output is not freely disposable – the regulated technology.

As we showed in Eq. (10), PAC is the index of maximum good output production when the bad output is unregulated to maximum good output production when the bad output is regulated. Hence, ΔPAC_t^{t+1} is an index of the *change* between period t and period $t+1$ in the amount of foregone good output due to the bad output not being freely disposable. It follows the change in PAC between period t and period $t+1$ is equivalent to the change in foregone good output production associated with pollution abatement in period t and period $t+1$. Therefore,[23]

$$\begin{aligned} \Delta\text{PAC}_t^{t+1} &= \left[\frac{G(x^{t+1}, t+1)/F(x^{t+1}, b^{t+1}, t+1)}{G(x^t, t)/F(x^t, b^t, t)}\right] \\ &= \left[\frac{G(x^{t+1}, t+1)/G(x^t, t)}{F(x^{t+1}, b^{t+1}, t+1)/F(x^t, b^t, t)}\right] \end{aligned} \tag{11}$$

If the value of ΔPAC_t^{t+1} exceeds unity, abatement costs increased between period t and period $t+1$. A value of less than unity signifies ΔPAC decreased. A value of unity indicates ΔPAC is unchanged between period t and period $t+1$.

Fig. 4 extends Fig. 3 by depicting the regulated and unregulated frontiers in period t and period $t+1$. The regulated frontier (0RSTV) and the unregulated frontier (WT) represent the combinations of good and bad outputs that can be produced by the inputs and technology available in period $t+1$. Point i represents the observed good output and bad output production in period $t+1$, and (sj'/sj) is the opportunity cost of pollution abatement in period $t+1$, where s is the observed bad output production in period $t+1$. In terms of the regulated and unregulated frontiers depicted in Fig. 4, the change in

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[17] Because plants already faced regulations prior to 1995, what we refer to as our “unregulated” technology is, in fact, a least regulated technology. We do not attempt to estimate – the hypothetical – unregulated technology that would have evolved in the absence of pollution abatement.

[18] There are two approaches to modeling free disposability of bad outputs. Färe and Grosskopf (1983) and numerous subsequent papers modeled free disposability by relaxing the constraint on the bad output(s) from “=” to “≥”. With this specification, the bad output(s) is treated in the same fashion as the good output(s). Eventually, a second specification of free disposability was proposed in which the bad output is excluded from the production technology (see Färe, Grosskopf, and Pasurka, 2007b). In this paper, we employ the second specification of free disposability.

[19] This depiction of the unregulated frontier corrects Färe, Grosskopf, and Pasurka (2007b).

[20] Not all points on the horizontal unregulated (i.e., free disposability) frontier depict combinations of good and bad outputs that can be produced with a given input vector and technology. Instead, the unregulated frontier reflects the maximum amount of the good output that can be produced by a given input vector and technology when the producer is allowed to ignore the bad outputs it generates.

[21] If pollution abatement is not undertaken, only the unregulated technology is relevant and all observations inside the production frontier are technically inefficient.

[22] In Fig. 3, B represents an observation where PAC equals unity (i.e., no reduced good output production is associated with pollution abatement).

[23] Because we specified a ratio of good output for the unregulated and regulated technologies, this determines the multiplicative nature of our decomposition.

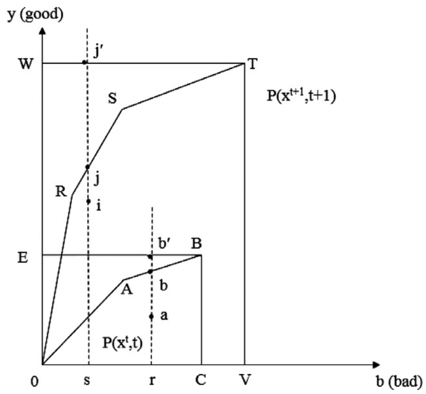

Fig. 4. Production frontiers in periods t and $t+1$.

PAC specified in Eq. (12) is:

$$\Delta\mathrm{PAC}_t^{t+1} = \left[\frac{(sj'/sj)}{(rb'/rb)}\right] = \left[\frac{(sj'/rb')}{(sj/rb)}\right] \tag{12}$$

In Fig. 4, it can be seen that inputs, bad output production, and the regulated technology determine good output production for the regulated technology, while inputs and the unregulated technology determine good output production for the unregulated technology. As a result, the change in the cost of pollution abatement between period t and period $t+1$ is determined by technical change, changes in the inputs, and changes in bad output production.[24]

Li and Chan (1999), which is discussed in Grosskopf (2003), extended the Färe, Grosskopf, and Lovell (1994) decomposition framework by specifying a methodology that allows changes in good output production to be decomposed into changes associated with technical efficiency change, technical change, and changes in inputs. The decomposition procedure we specify includes two modifications to the Li and Chan framework. First, we include bad outputs. Second, because we are interested in the factors affecting the foregone good output due to the lack of bad output free disposability, we introduce a new factor – changes in bad output production – to explain changes in the maximum good output that can be produced by the regulated or unregulated frontiers with a given technology and input vector.

In the following decomposition, Eq. (11) is rewritten as a series of environmental production functions. In order to avoid selecting an arbitrary base period, we use geometric means of period t and period $t+1$ as reference technologies when specifying mixed-period LP problems:

$$\begin{aligned}
\Delta\mathrm{PAC}_t^{t+1} &= \left[\frac{G(x^{t+1},t+1)/G(x^t,t)}{F(x^{t+1},b^{t+1},t+1)/F(x^t,b^t,t)}\right]\\
&= \left(\left[\frac{G(x^{t+1},t+1)/G(x^{t+1},t)}{F(x^{t+1},b^{t+1},t+1)/F(x^{t+1},b^{t+1},t)}\right]^{1/2}\right.\\
&\quad\times\left.\left[\frac{G(x^t,t+1)/G(x^t,t)}{F(x^t,b^t,t+1)/F(x^t,b^t,t)}\right]^{1/2}\right)\\
&\quad\times\left(\left[\frac{G(x^{t+1},t)/G(x^t,t)}{F(x^{t+1},b^{t+1},t)/F(x^t,b^{t+1},t)}\right]^{1/2}\right.\\
&\quad\times\left.\left[\frac{G(x^{t+1},t+1)/G(x^t,t+1)}{F(x^{t+1},b^t,t+1)/F(x^t,b^t,t+1)}\right]^{1/2}\right)\\
&\quad\times\left(\left[\frac{G(x^t,t)/G(x^t,t)}{F(x^t,b^{t+1},t)/F(x^t,b^t,t)}\right]^{1/2}\right.\\
&\quad\times\left.\left[\frac{G(x^{t+1},t+1)/G(x^{t+1},t+1)}{F(x^{t+1},b^{t+1},t+1)/F(x^{t+1},b^t,t+1)}\right]^{1/2}\right)\\
&= (\mathrm{TC}_u/\mathrm{TC}_r)\times(\mathrm{IC}_u/\mathrm{IC}_r)\times(\mathrm{BP}_u/\mathrm{BP}_r)
\end{aligned} \tag{13}$$

where $(\mathrm{TC}_u/\mathrm{TC}_r)$ represents the change in PAC associated with technical change (TC), $(\mathrm{IC}_u/\mathrm{IC}_r)$ is the change in PAC associated with input changes (IC), and $(\mathrm{BP}_u/\mathrm{BP}_r)$ represents the change in PAC associated with changes in bad output production (BP).[25] Within the three sets of parentheses, the expression in the first set of brackets calculates ΔPAC using period t as the reference technology for mixed-period LP problems, while the expression in the second set of brackets calculates ΔPAC using period $t+1$ as the reference technology for mixed-period LP problems.

More specifically, $(\mathrm{TC}_u/\mathrm{TC}_r)$ is the change in good output production due to technical change in the unregulated technology relative to the change in good output production due to technical change in the regulated technology.[26] $(\mathrm{IC}_u/\mathrm{IC}_r)$ is the change in good output production by the unregulated technology due to changes in input levels relative to the change in good output production by the regulated technology due to input changes. Hence, the TC and IC components reflect changes between period t and period $t+1$ in the amount of good output production foregone as a result of the lack of bad output free disposability, while the BP component reflects changes in good output production associated with movements along the regulated frontiers of period t and period $t+1$.[27] The BP component reflects movement along the regulated frontier because the $G(\bullet)$ components cancel out each other, and only the $F(\bullet)$ components in the denominator remain.

For TC, IC, and BP, a value exceeding unity indicates the component is associated with increasing ΔPAC between period t and period $t+1$. A value less than unity signifies the component is associated with declining ΔPAC. Finally, a value of unity indicates the component is associated with no change in ΔPAC.

4. Data and results

In the previous sections, environmental production functions, which model the joint production of good and bad outputs, were introduced as a means of determining the foregone good output due to the lack of bad output free disposability (i.e., PAC). It was then possible to specify the environmental production functions as LP programs and determine how to calculate changes in PAC and the relative importance of the factors associated with changes in PAC.

In this section, we discuss the data and the accompanying empirical results. Our data consist of annual observations for coal-fired power plants from 1995 to 2005. The technology modeled in this study consists of one good output, "net electrical generation" (kWh), and one bad output, sulfur dioxide (SO_2).[28] The inputs consist of the capital stock, the number of employees, and the heat content (in Btu)

[24] An alternative definition of abatement intensity maintains the observed mix of good and bad outputs (see Färe, Grosskopf, and Pasurka, 1986). The selection of the measure of pollution abatement intensity will influence the results of our decomposition.

[25] If pollution abatement is not undertaken, only the unregulated technology is relevant and all observations inside the production frontier are technically inefficient.

[26] Whether the PAC (which is shown by the distance between the unregulated and regulated frontiers) increases or decreases between period t and period $t+1$ depends upon the relative shifts in the unregulated and regulated frontiers. For example, if the maximum good output produced by the unregulated frontier increases at a faster rate than maximum good output produced by the regulated technology, then PAC will increase between period t and period $t+1$. On the other hand, if the maximum good output produced by the unregulated frontier increases at a slower rate than maximum good output produced by the regulated technology, then PAC will decrease between period t and period $t+1$.

[27] A figure that extends Fig. 4 and illustrates the decomposition is available in Appendix A.

[28] The empirical section of this paper is designed to provide a relatively simple example of the decomposition model. Decomposing the total opportunity costs when

Table 2
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
Capital stock	Dollars (in millions, 1973$)	290	195	863	57
Employees	Workers	214	136	578	42
Heat content of coal	Btu (in billions)	57,064	47,174	193,574	2255
Heat content of oil	Btu (in billions)	109	116	514	0
Heat content of gas	Btu (in billions)	93	284	2083	0
80 coal-fired power plants, 2005					
Electricity	kWh (in millions)	6647	5249	22,338	176
SO_2	Short tons (in thousands)	34	33	186	1
Capital stock	Dollars (in millions, 1973$)	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

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 percent of the Btu of fuels consumed by each plant.[29] FERC Form 1 (U.S. Federal Energy Regulatory Commission, various years) is the source of labor and capital data for private electric power plants, while the EIA-412 survey (U.S. Department of Energy, various years-a) is the source of labor and capital data for public power plants. [30] In addition to the increasing number of private utilities not reporting capital and labor data, the DOE halted the EIA-412 survey after 2003. However, the Tennessee Valley Authority voluntarily posted 2004–06 data for its electric power plants on-line.[31] The U.S. Department of Energy's (DOE) Form EIA-767 survey (see U.S. Department of Energy, various years-b) is the source of information about fuel consumption, and net generation of electricity. The SO_2 emission data are collected by the U.S. EPA Continuous Emissions Monitoring System (CEMS). The sample consists of a balanced panel of 80 power plants for 1995–2005. Contemporaneous frontiers are used when modeling the production technology. This means the period $t + 1$ technology consists of observations from period $t + 1$, while the period t technology consists of observations from period t. As a result, there are ten two-year pairs from 1995–96 to 2004–05 associated with each power plant. Table 2 presents summary statistics of the data for 1995 and 2005.[32] The 27 percent decline in SO_2 emissions per kWh exhibited by the average plant in our sample is almost an exact match with the industry data reported in Table 1. As with other economic analyses that quantify the cost of government policies (e.g., taxes and tariffs), these results are a reflection of the production technologies assumed in the model.

Table 3
Decomposition of ΔPAC for two-year pairs (80 coal-fired plants) (**BOLD = maximum** value and ***ITALICS = minimum*** value).

Two-year pairs	ΔPAC	TC	IC	BP
1995–96	1.0000	1.0075	1.0058	***0.9868***
1996–97	0.9979	0.9940	1.0057	0.9982
1997–98	***0.9951***	0.9976	0.9989	0.9986
1998–99	1.0021	0.9996	0.9966	1.0059
1999–00	1.0037	0.9960	**1.0104**	0.9973
2000–01	**1.0060**	**1.0085**	***0.9942***	1.0034
2001–02	0.9961	0.9934	0.9984	1.0043
2002–03	1.0045	0.9940	0.9972	**1.0135**
2003–04	1.0026	0.9930	1.0069	1.0027
2004–05	0.9978	***0.9915***	1.0043	1.0020
Geometric means	1.0006	0.9975	1.0018	1.0013

Note: Subtracting unity from values in this table yield percentage changes.
PAC = index of change in pollution abatement costs.
TC = index of change in pollution abatement costs associated with technical change.
IC = index of change in pollution abatement costs associated with change in input vector.
BP = index of change in pollution abatement costs associated with change in bad output.

ΔPAC and its components are presented in Table 3 and Fig. 5 for each two-year period. In 1995, the geometric mean of the PAC for the 80 plants is 1.0199. Of the 80 plants, 32 had PAC of unity (no opportunity costs associated with reducing SO_2 emissions) in 1995 and Carbon (3644) had the maximum PAC of 1.2107. For plants in our sample, SO_2 emissions/kWh declined by 27 percent between 1995 and 2005, the annual increase in PAC was only 0.06 percent between 1995 and 2005. As a result, in 2005 the geometric mean of the PAC for the 80 plants is 1.0257. In 2005, 35 plants had PAC of unity and Dave Johnston (4158) had the maximum PAC of 1.2161. TC was the only component

regulating multiple bad outputs is a straightforward extension of the model. However, attempting to identify the change in opportunity costs associated with individual bad outputs when modeling multiple bad outputs is more challenging due to the varying relationships among the bad outputs (see, Färe, Grosskopf, Pasurka, & Weber, 2012).

[29] 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 percent 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 percent of a plant's fuel consumption.

[30] 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.

[31] 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, Burtraw, Cropper, and Palmer (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.

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

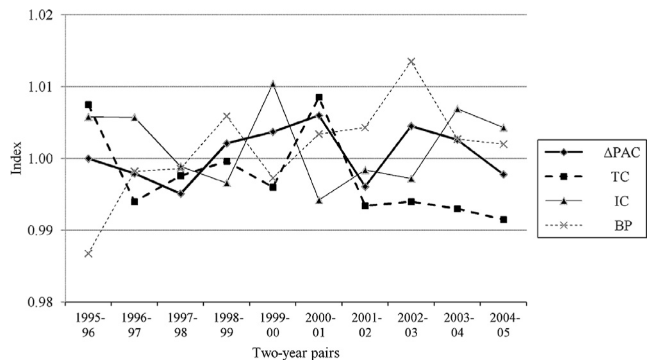

Fig. 5. Changes in PAC and its components (1995–2005).
Note:
PAC = index of change in pollution abatement costs.
TC = index of change in pollution abatement costs associated with technical change.
IC = index of change in pollution abatement costs associated with change in input vector.
BP = index of change in pollution abatement costs associated with change in bad output.

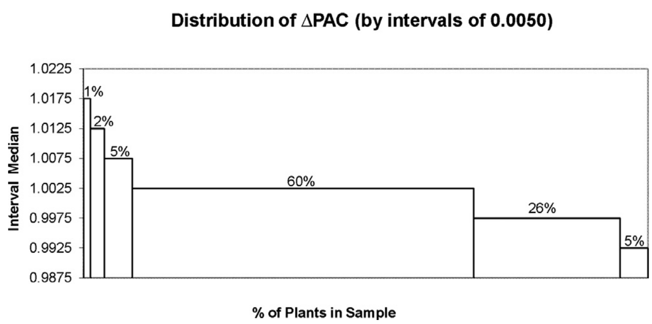

Fig. 6. Salter Diagram of Changes in PAC.

associated with reducing PAC during the entire 1995–2005 period. TC is associated with an annual decrease in PAC of 0.25 percent, while IC is associated with an annual increase in PAC of 0.18 percent. Finally, BP is associated with an annual increase in PAC of 0.13 percent.

The decline in PAC associated with TC reflects differences in shifts of the unregulated and regulated frontiers. In fact, our finding may reflect a reallocation of R&D resources to production activities that produce reduced quantities of SO_2. Because regulations discourage the use of the bad-output-intensive production technology, plants adopt technology that simultaneously expands good output production while reducing bad output production. This results in the regulated production frontier shifting outward toward the northwest. This has the effect of reducing the foregone good output due to the lack of bad output free disposability. Because the regulated production frontier is expanding more rapidly than the unregulated technology, there is a decrease in the amount of the good output foregone due to the lack of bad output free disposability – and the associated values of ΔPAC are less than unity. Hence, it is possible to observe values of ΔPAC that are less than unity occurring simultaneously with reduced bad output production in period $t + 1$ relative to period t.

Table 4 presents the average annual results for ΔPAC and its components for the individual power plants. The mean values for the ΔPAC index of plants ranged from 0.9908 for Carbon (3644) to 1.0175 for Dave Johnston (4158). Mean values of TC for individual plants range from 0.9328 for Valmont (477) to 1.0211 for F.B. Culley (1012). The range of mean values of IC extended from 0.9723 for Cumberland (3399) to 1.0298 for Cholla (113). For BP, mean values for power plants ranged from 0.9584 for F.B. Culley (1012) to 1.0722 for Mount Storm (3954). The dispersion of the ΔPAC results are depicted via a Salter diagram (see Fig. 6). Sixty percent of the plants fall in the interval

Table 4
Geometric Means of 10 two-year pairs between 1995–96 and 2004–05 (**BOLD = maximum** value and ***ITALICS*** = ***minimum*** value).

Plant name	Plant ID	ΔPAC	TC	IG	BP
Barry	3	1.0000	0.9997	1.0001	1.0001
Gorgas	8	1.0000	1.0000	1.0000	1.0000
Colbert	47	1.0030	1.0000	1.0008	1.0022
Widows Creek	50	1.0020	1.0002	0.9981	1.0037
Cholla	113	0.9953	0.9761	**1.0298**	0.9902
Cherokee	469	1.0114	0.9817	1.0053	1.0248
Comanche	470	0.9990	1.0038	1.0009	0.9943
Valmont 5	477	1.0017	***0.9328***	1.0283	1.0443
Smith	643	1.0000	0.9999	1.0031	0.9969
Bowen	703	1.0000	1.0003	1.0019	0.9978
Hammond	708	0.9998	1.0003	1.0002	0.9993
Mitchell	727	1.0000	1.0000	1.0001	0.9999
Joppa Steam	887	0.9977	0.9943	1.0017	1.0017
Tanners Creek	988	1.0000	1.0000	1.0000	1.0000
Bailly	995	1.0038	0.9990	1.0122	0.9928
Cayuga	1001	1.0000	1.0000	1.0000	1.0000
R. Gallagher	1008	1.0000	1.0000	1.0000	1.0000
F.B. Culley	1012	0.9948	**1.0211**	1.0165	***0.9584***
M.L. Kapp	1048	1.0000	0.9970	1.0014	1.0016
Riverside	1081	1.0020	1.0002	1.0036	0.9982
LaCygne	1241	1.0001	0.9980	1.0021	1.0000
Big Sandy	1353	1.0000	1.0000	0.9996	1.0004
E.W. Brown	1355	1.0000	1.0000	1.0003	0.9997
Ghent	1356	1.0016	0.9991	0.9997	1.0027
Green River	1357	1.0000	1.0000	1.0000	1.0000
Cane Run	1363	0.9994	1.0005	1.0004	0.9986
Mill Creek	1364	1.0012	0.9970	1.0055	0.9988
Paradise	1378	1.0026	1.0003	0.9819	1.0208
Shawnee	1379	1.0079	0.9988	1.0055	1.0036
Monroe	1733	1.0002	1.0005	0.9997	1.0000
St. Clair	1743	1.0044	1.0027	1.0021	0.9996
High Bridge	1912	0.9995	1.0053	0.9999	0.9943
Asheville	2706	1.0010	1.0007	0.9999	1.0003
H.F. Lee	2709	0.9996	1.0000	1.0016	0.9980
L.V. Sutton	2713	1.0003	0.9997	1.0014	0.9992
G.G. Allen	2718	0.9991	1.0002	1.0028	0.9962
Buck	2720	1.0028	1.0008	1.0044	0.9976
Cliffside	2721	1.0000	0.9999	1.0016	0.9984
Dan River	2723	1.0013	1.0008	0.9995	1.0011
Marshall	2727	1.0000	1.0002	1.0048	0.9951
Riverbend	2732	0.9924	1.0003	1.0217	0.9710
Muskingum River	2872	1.0000	1.0000	1.0000	1.0000
Lee	3264	0.9999	1.0001	1.0027	0.9971
McMeekin	3287	1.0000	0.9977	1.0018	1.0005
Watertree	3297	0.9999	1.0000	1.0001	0.9999
Williams	3298	1.0004	0.9993	1.0025	0.9986
Bull Run	3396	1.0000	0.9998	1.0007	0.9995
Cumberland	3399	1.0005	1.0051	***0.9723***	1.0237
Gallatin	3403	1.0052	1.0002	0.9982	1.0068
John Sevier	3405	1.0061	0.9916	0.9948	1.0199
Johnsonville	3406	1.0000	1.0000	1.0000	1.0000
Kingston	3407	1.0011	0.9998	1.0003	1.0010
Carbon	3644	***0.9908***	1.0020	0.9856	1.0032
Clinch River	3775	0.9992	1.0015	1.0001	0.9976
Glen Lyn	3776	0.9999	1.0000	0.9996	1.0003
Bremo Bluff	3796	0.9998	0.9999	0.9996	1.0004
Chesterfield	3797	1.0000	1.0000	1.0000	1.0000
Chesapeake	3803	1.0000	1.0002	1.0001	0.9997
Amos	3935	1.0001	1.0000	1.0021	0.9980
Kanawha River	3936	0.9997	0.9978	1.0108	0.9912
Sporn	3938	1.0000	1.0000	0.9998	1.0002
Rivesville	3945	0.9998	0.9998	0.9965	1.0035
Mount Storm	3954	1.0110	0.9353	1.0082	**1.0722**
Pulliam	4072	0.9976	1.0033	1.0021	0.9923
Weston	4078	0.9983	1.0018	0.9989	0.9975
Dave Johnston	4158	**1.0175**	1.0150	0.9996	1.0029
Naughton	4162	1.0000	1.0028	0.9967	1.0006
James H. Miller Jr.	6002	1.0046	0.9844	1.0130	1.0075
R.M. Schaffer	6085	0.9997	0.9961	0.9980	1.0057
A.B. Brown	6137	1.0006	0.9977	1.0016	1.0013
Welsh	6139	0.9923	0.9916	1.0026	0.9981

(*continued on next page*)

Table 4 (*continued*)

Plant name	Plant ID	△PAC	TC	IG	BP
Harrington	6193	1.0000	0.9944	0.9948	1.0109
Tolk Station	6194	1.0000	0.9962	0.9952	1.0087
Pawnee	6248	0.9965	1.0004	0.9952	1.0009
Mountaineer	6264	1.0010	0.9988	1.0051	0.9971
Belews Creek	8042	1.0000	1.0006	1.0015	0.9979
Jim Bridger	8066	1.0051	0.9888	1.0101	1.0063
Huntington	8069	0.9953	1.0045	0.9953	0.9954
General James M. Gavin	8102	1.0004	0.9777	1.0233	0.9999
Valmy	8224	0.9995	1.0091	1.0009	0.9897
Geometric means		1.0006	0.9975	1.0018	1.0013

Note: Subtracting unity from values in this table yield percentage changes.
PAC = index of change in pollution abatement costs.
TC = index of change in pollution abatement costs associated with technical change.
IC = index of change in pollution abatement costs associated with change in input vector.
BP = index of change in pollution abatement costs associated with change in bad output.

of △PAC values from 1.0000 to 1.0049. Since slightly more than half of the plants in this interval have △PAC values of unity, the share of plants with positive △PAC values between 1.0001 and 1.0049 is close to the share of plants – 26 percent – in the interval with △PAC values from 0.9950 to 0.9999. In addition, 5 percent of the plants fall in the 1.0050 to 1.0099 interval and another 5 percent of the plants fall in the 0.9900 to 0.9949 interval. The remaining 3 percent of the plants fall in the intervals: 1.0100–1.0149 and 1.0150–1.0199.

5. Conclusions

In this study, we specified a technology that models the joint production of good and bad outputs. We then specified a decomposition procedure to investigate the relative importance of the factors associated with changes in pollution abatement costs.

This study addressed the question of whether the decline in bad output production depicted in Table 1 was purchased at the cost of substantial forgone good output production – the opportunity cost of pollution abatement. A sample of 80 coal-fired electric power plants in the United States between 1995 and 2005 was used to calculate PAC and the relative importance of technical change, input growth, and changes bad output production in explaining changes in PAC. Since any decomposition procedure is somewhat arbitrary, caution should be exercised when interpreting the results, which are influenced by the factors such as the number of inputs and bad outputs specified in the production technology. Nevertheless, we did demonstrate that it is possible to determine the relative importance of factors associated with changes in PAC within a formal model of the joint production of good and bad outputs.

Our model highlights the fact that specifying the regulated and unregulated technologies can be used to calculate PAC and changes in PAC. Since an increasing share of pollution abatement activities involve process changes, survey techniques encounter increasing difficulty in obtaining accurate estimates of PAC. While the decomposition of the relative importance of the factors that affect PAC is relatively easy to specify within a joint production framework, it is difficult to implement when using traditional survey estimates of PAC.

In addition to providing a framework for determining the relative importance of factors associated with changes in PAC, it also provides a framework for thinking about the factors associated with discrepancies between ex ante forecasts of regulatory costs, and the observed ex post PAC.[33] Among the explanations offered for the discrepancies (see MacLeod, Moran, Aresti, Harrington, & Morgenstern, 2006, pp. 32–35) are (1) using conservative assumptions about technical change, (2) inaccuracy in compliance and implementation estimates (i.e., observed emission-intensity differs from forecasted emission-intensity), (3) baseline issues, and (4) economies of scale. While there may be human biases in determining ex ante PAC estimates[34], we will focus on how our model can be used to identify discrepancies between ex ante and ex post PAC that are associated with the underlying production technology.

If we interpret PAC in period t as a proxy for ex ante PAC forecasts and PAC in period $t+1$ as a proxy for ex post PAC, discrepancies between ex ante and ex post PAC can be seen as the result of changes in the factors associated with changes in PAC. It follows that if the ex ante forecast of PAC is based on erroneous forecasts of input growth, good–bad output intensity, or technical change, ex post PAC will differ from the ex ante forecasts. For example, unanticipated increases (decreases) in the scale of operation (i.e., input changes) will result in ex post PAC being higher (lower) than the ex ante estimates. Therefore, an investigation of ex ante and ex post cost differences would require information about forecasted changes in inputs, regulatory intensity, and regulated and unregulated technical change.

In summation, we believe the decomposition strategy proposed in this paper offers insights on the factors affecting pollution abatement costs that have heretofore not been available. The results offer evidence of the role played by technical change in moderating expected increases in production costs associated with stricter regulations on bad output production. In addition, it suggests a strategy for addressing at least some of the sources of discrepancies between ex ante and ex post estimates of PAC.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2015.07.040.

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[33] Harrington, Morgenstern, and Nelson (2000) assembled data on 28 rules, of which 13 were promulgated by the U.S. Environmental Protection Agency, in a study of the association between ex ante and ex post estimates of environmental regulations. More recently, MacLeod et al. (2006) conducted an extensive survey of studies that compare ex ante and ex post compliance costs.

[34] For example, the regulated community may have an incentive to overestimate PAC associated with a proposed regulation.

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