

Decomposing electric power plant emissions within a joint production framework [☆]

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Abstract

This study calculates the relative importance of factors associated with changes in NO_x and SO₂ emissions by coal-fired electric power plants between 1987 and 1995 using distance functions to model the joint production of good and bad outputs. This new decomposition model calculates changes in emissions (the bad outputs) associated with changes in technical efficiency, technical change, growth of fuel and non-fuel inputs, and changes in the mix of good and bad outputs. This study finds that declining SO₂ emissions are primarily associated with changes in the output mix, while declining NO_x emissions are associated with declining fuel consumption and changes in the output mix.

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1. Introduction

While it is possible to assess the effectiveness of pollution abatement activities by observing changes in bad output production, a shortcoming of this approach is that factors other than environmental regulations are associated with bad output production.¹ For example, an

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¹ Throughout this study, “good” output refers to the marketed good produced by an industry and “bad” output refers to emissions of a pollutant.

expanding industry increases its bad output production if it uses a technology that produces a constant mix of good and bad outputs.² Hence, simply observing changes in bad output production may not reveal the effect of pollution abatement activities on bad output production.

This study models the joint production of good and bad outputs and calculates the relative importance of technical change, changes in technical efficiency, changes in fuel consumption, changes in non-fuel inputs, and changes in emission intensity. Because it models a technology in which good and bad outputs are jointly produced and pollution abatement activities other than fuel switching or substituting non-energy inputs for energy inputs exist, this study differs from models specified in previous studies of the factors associated with changes in bad output production. In fact, this study decomposes changes in bad output production in a manner that is comparable to growth accounting studies of the relative importance of factors associated with changes in good output production (i.e., total factor productivity).

The remainder of this study is organized in the following manner. Section 2 surveys previous studies, while Section 3 derives the joint production decomposition model used in this study. Section 4 presents the results and Section 5 summarizes this study and discusses potential extensions.

2. Previous decomposition studies

This section reviews previous studies of factors associated with changes in bad output production. Studies that assign changes in bad output production to various factors are said to “decompose” these changes. For the purposes of this study, index decomposition (ID) models use annual data to calculate the relative importance of factors associated with changes in bad output production, while structural decomposition analysis (SDA) models are constructed around input–output tables.³ Six studies using the ID method (Lin and Chang, 1996; Selden et al., 1999; Viguier, 1999; Hammer and Löfgren, 2001; Bruvoll and Medin, 2003; Cherp et al., 2003) and four studies using variations of the SDA method (Leontief and Ford, 1972; Meyer and Stahmer, 1989; Wier, 1998; Wier and Hasler, 1999) have estimated the relative importance of factors associated with changes in bad output production when pollution abatement activities—other than fuel switching or substituting other inputs for energy—exist.⁴ With bad output production such as CO₂ emissions, the production frontier consists of a single combination of good and bad output production for a given technology and input bundle. This occurs because reducing CO₂ emissions requires either substituting among fuels or substituting non-fuel inputs for fuel inputs which results in a different set of inputs being employed by the producer. However, when bad outputs such as SO₂ or NO_x emissions are produced, pollution abatement activities allow multiple combinations of good and bad outputs to be produced by a given technology and input bundle. For example, given quantities of capital and labor can be used to produce electricity or they can be reallocated to pollution abatement activities which result in reduced good and bad output production.⁵

² The mix of good and bad outputs refers to the quantity of bad output produced per unit of the good output (i.e., the emission intensity of a process).

³ Hoekstra and van der Bergh (2003) compared the SDA and ID models.

⁴ Both methodologies have been used to investigate the factors associated with changes in CO₂ emissions and energy consumption. Rose and Casler (1996) and Rose (1999) surveyed the SDA literature, while Ang (1999) and Ang and Zhang (2000) surveyed the ID literature.

⁵ Zaim (2004) specified a joint production model to investigate the factors associated with changes in emission intensities (i.e., the quantity of bad output produced per unit of good output produced).

Aiken and Pasurka (2002) specified a joint production model, and determined the extent of changes in SO₂ production (i.e., the bad output) associated with changes in technical efficiency, changes in good output production, and changes in the output mix of manufacturing industries in the United States between 1985 and 1996 and between 1990 and 1996. They also calculated changes in bad output production associated with changes in good output production and changes in the output mix using a procedure that was comparable to the ID and SDA models. A comparison of the results revealed that the availability of pollution abatement activities other than fuel switching or substituting other inputs for energy may cause the ID and SDA models to produce biased results due to the imposition of restrictions on the production technologies.

Using data for two-digit standard industrial classification (SIC) manufacturing industries from 1970 to 1996, Pasurka (2003) extended Aiken and Pasurka (2002) and calculated the association between changes in SO₂ emissions and changes in technical efficiency, technical change, input growth, and changes in the output mix. He also calculated the change in SO₂ emissions associated with the inability of producers to freely dispose of SO₂ emissions. Pasurka found that changes in the output mix was the factor most closely associated with changes in SO₂ emissions. This study differs from Pasurka (2003) in the several respects. Instead of time series data for manufacturing, panel data consisting of coal-fired electric power plants are employed. Second, changes in the production of two bad outputs are simultaneously modeled. Finally, Pasurka (2003) specified a different benchmark technology than the one this study employs.

3. Joint production decomposition model

This section introduces distance functions to model the joint production of good and bad outputs. To accomplish this, technologies that model the joint production of good and bad outputs based on the assumption of weak disposability of the bad outputs are specified.⁶ The weak disposability technology, which assumes the producer may not freely dispose of its bad outputs, can be viewed as the regulated technology. This technology represents the case when a producer implements pollution abatement activities. Hence, good output production declines as inputs are reallocated to activities that reduce bad output production.

In this study, a technology consists of the set of processes available to the k' producer. Each process represents a fixed relationship among inputs (x), good outputs (y), and bad outputs (b). Linear combinations of processes may be employed subject to the appropriate LP constraints. The regulated technology for period t , $S_r^t(x^t)$, is formally specified as (see Färe et al., 1994a):⁷

$$S_r^t(x^t) = \{(y^t, b^t): \begin{aligned} &\sum_{k=1}^K z_k y_{km}^t \geq y_m^t & m = 1, \dots, G \\ &\sum_{k=1}^K z_k b_{ki}^t = b_i^t & i = 1, \dots, B \\ &\sum_{k=1}^K z_k x_{kn}^t \leq x_n^t & n = 1, \dots, N \\ &z_k \geq 0 & k = 1, \dots, K \end{aligned} \} \quad (1)$$

⁶ This study assumes that good outputs are freely disposable (see Färe et al., 1986, 1989).

⁷ Throughout this study, the subscript r signifies the regulated technology.

where the z^t are weights assigned to each of the k observations (i.e., processes) in period t used to construct the production frontier. The first set of constraints is associated with good outputs, and there is a separate constraint for each of the G good outputs of producer k' . The inequality sign imposes the assumption of free disposability on good outputs. The second set of constraints is associated with bad outputs, and there is a separate constraint for each of the B bad outputs. The equality sign imposes the assumption of weak disposability on bad outputs. The third set of constraints is associated with inputs, and there is a separate constraint for each of the N inputs. Finally, a non-negativity constraint is imposed on the z_k in (1). Because the sum of the intensity parameters (i.e., the z_k) is unconstrained, constant returns to scale are assumed.⁸

In addition, good and bad outputs are assumed to be null-joint (i.e., good output production results in bad output production) if (see Färe et al., 2001):

$$\begin{aligned} \text{(a)} \quad & \sum_{k=1}^K b_{ki}^t > 0 \quad i = 1, \dots, B \\ \text{(b)} \quad & \sum_{i=1}^B b_{ki}^t > 0 \quad k = 1, \dots, K \end{aligned} \quad (2)$$

Condition (2a) states that each bad output must be emitted by at least one producer, while (2b) states that each producer must emit at least one bad output. If it is assumed that each $b_i^t = 0$ for the unregulated technology (1), then (2) requires that each z_k be zero, which implies that production of each good output y_m^t be zero.

Using distance functions, Färe et al. (1994b) specified a procedure that assigned productivity changes to changes in technical efficiency and technical change. Li and Chan (1998) extended Färe et al. (1994b) by assigning output changes to technical change, changes in technical efficiency, and changes in inputs.⁹ The decomposition procedure specified in this study makes three modifications to the Li and Chan decomposition framework. First, bad outputs are introduced and assumed to be weakly disposable for the regulated technology. Second, the Li and Chan framework is modified to allow for changes in different types of inputs. Finally, the Li and Chan framework is modified to allow changes in the output mix to affect bad output production.

Like Färe and Grosskopf (1983) and Färe et al. (1986), this study specifies an output-based radial measure of technical efficiency that assumes the producer maintains its observed mix of good and bad outputs. As a result, production occurs along the process ray that includes the observed production of good and bad outputs. Since good and bad outputs are treated symmetrically, technical change, input growth, and changes in technical efficiency are associated with proportional changes in good and bad outputs.¹⁰

Six different output-based distance functions are required to implement the decomposition model specified in this study. The first is (see Färe et al., 1994b):

$$D_{\text{or}}^t(x^t, y^t, b^t) = \inf \{ \theta : (x^t, y^t/\theta, b^t/\theta) \in S_r^t(x^t) \} \quad (3)$$

⁸ Färe et al. (1986) modeled a variable return to scale technology with bad outputs.

⁹ Grosskopf (2003, pp. 469–470) summarizes the Li and Chan decomposition model.

¹⁰ Treating the good and bad outputs asymmetrically assumes an inefficient producer using a process that produces less of the bad output per unit of the good output than its observed process (see Färe et al., 1989, 2001).

Its value, θ , is the reciprocal of the maximum proportional expansion of the observed production of good (y^t) and bad outputs (b^t) that is possible with the regulated technology, $S_r^t(x^t)$, and inputs (x^t) available in period t . When $D_o^t(x^t, y^t, b^t) < 1$, the observation is technically inefficient (i.e., inside the production frontier) while $D_o^t(x^t, y^t, b^t) = 1$ indicates the observation is technically efficient (i.e., on the production frontier). A similar interpretation exists for $D_{or}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})$.

The third output–distance function is a mixed-period distance function:

$$D_{or}^t(x^{t+1}, y^{t+1}, b^{t+1}) = \inf \{ \theta : (x^{t+1}, y^{t+1}/\theta, b^{t+1}/\theta) \in S_r^t(x^{t+1}) \} \quad (4)$$

Its value is the reciprocal of the maximum proportional change of the good and bad outputs needed to make the inputs and outputs of period $t+1$ (i.e., $(x^{t+1}, y^{t+1}, b^{t+1})$) feasible relative to the regulated technology of period t . A similar expression exists for $D_{or}^{t+1}(x^t, y^t, b^t)$. The value of the fifth distance function, $D_{or}^{t+1}(x^{t+1}, y^t, b^t)$, is the reciprocal of the maximum proportional change of the good and bad outputs needed to make period $t+1$ inputs and period t outputs (i.e., (x^{t+1}, y^t, b^t)) feasible relative to the period $t+1$ regulated technology. A similar interpretation exists for $D_{or}^t(x^t, y^{t+1}, b^{t+1})$.

In Fig. 1, the regulated frontier 0JKBC represents combinations of good and bad outputs that can be produced by the period t input vector and technology. Since the model allows a producer to be technically inefficient, the maximum production of the i th bad output that can be produced by the regulated technology in period t , B_{ri}^t , is determined by scaling the observed production of the i th bad output, b_i^t , by the level of technical efficiency, θ_r^t , which represents the proportional expansion of good and bad outputs required to project an observation (0a) from inside the frontier to the regulated frontier (0b).¹¹ Hence, P_t represents the process employed by the producer in period t . From (4) it is known that $D_{or}^t(x^t, y^t, b^t)$ equals θ_r^t . Hence, B_{ri}^t can be expressed as:

$$B_{ri}^t = \frac{b_i^t}{\theta_r^t} = \frac{b_i^t}{D_{or}^t(x^t, y^t, b^t)} \quad (5)$$

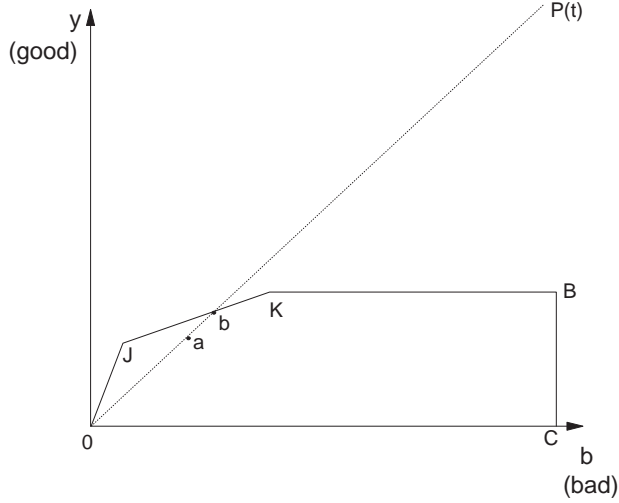
In period t , b_i^t is the quantity of bad output produced, while b_i^{t+1} represents bad output production in period $t+1$. As a result, the index of change in bad output production is:

$$\Delta \text{EMIT}_i = \frac{b_i^{t+1}}{b_i^t} \quad (6)$$

If ΔEMIT_i exceeds (is less than) unity, there is an increase (decrease) in production of the i th bad output, while a value of unity indicates no change between period t and period $t+1$. Fig. 2 extends Fig. 1 by adding the regulated frontier 0QRSIC for period $t+1$. The period $t+1$ process, P_{t+1} , produces less of the bad output per unit of good output than P_t . 0i is the observed level of production in period $t+1$. In Fig. 2, the index of change in production of the i th bad output is:

$$\Delta \text{EMIT}_i = \frac{0i}{0a} \quad (7)$$

¹¹ b_i^t is production of the i th bad output, while b^t is a vector of production of all bad outputs in period t . Hence, b_i^t is component of b^t .

Fig. 1. Regulated frontier in period t .

Finally, an expression is derived for ΔEMIT_i in terms of distance functions. Multiplying the numerator of Eq. (6) by $(D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})/D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}))$ and the denominator by $(D_{\text{or}}^t(x^t, y^t, b^t)/D_{\text{or}}^t(x^t, y^t, b^t))$ yields:

$$\Delta \text{EMIT}_i = \frac{b_i^{t+1}}{b_i^t} = \frac{D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})(b_i^{t+1}/D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1}))}{D_{\text{or}}^t(x^t, y^t, b^t)(b_i^t/D_{\text{or}}^t(x^t, y^t, b^t))} \quad (8)$$

which can be rewritten as:

$$\begin{aligned} \Delta \text{EMIT}_i &= \left[\left(\frac{D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\text{or}}^t(x^t, y^t, b^t)} \right) \right] \left[\left(\frac{D_{\text{or}}^t(x^t, y^t, b^t)}{D_{\text{or}}^{t+1}(x^t, y^t, b^t)} \right) \left(\frac{D_{\text{or}}^t(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \right) \right]^{1/2} \\ &\times \left[\left(\frac{D_{\text{or}}^{t+1}(x^t, y^t, b^t)}{D_{\text{or}}^{t+1}(x^{t+1}, y^t, b^t)} \right) \left(\frac{D_{\text{or}}^t(x^t, y^{t+1}, b^{t+1})}{D_{\text{or}}^t(x^{t+1}, y^{t+1}, b^{t+1})} \right) \right]^{1/2} \\ &\times \left[\left(\frac{b_i^{t+1}/D_{\text{or}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{b_i^t/D_{\text{or}}^{t+1}(x^{t+1}, y^t, b^t)} \right) \left(\frac{b_i^{t+1}/D_{\text{or}}^t(x^t, y^{t+1}, b^{t+1})}{b_i^t/D_{\text{or}}^t(x^t, y^t, b^t)} \right) \right]^{1/2} \end{aligned} \quad (9)$$

The expressions in the four sets of brackets in Eq. (9) can be interpreted as:

$$\Delta \text{EMIT}_i = \text{TE}_i \times \text{TC}_i \times \text{IG}_i \times \text{OM}_i \quad (10)$$

where TE represents the index of change in bad output production associated with changes in technical efficiency, TC represents the index of change in bad output production associated with technical change, IG represents the index of change in bad output production associated with input growth, and OM represents the index of change in bad output production associated with output mix changes. While the TE, TC, and IG factors have identical effects on all bad outputs being produced, the OM affect varies among the bad outputs. Hence, the OM factor accounts for the variation in ΔEMIT among the bad outputs emitted by a producer. For TE, TC, IG, and OM, a value exceeding unity indicates that increased bad output production between periods t and $t+1$ is associated with that component, while a value less than unity indicates

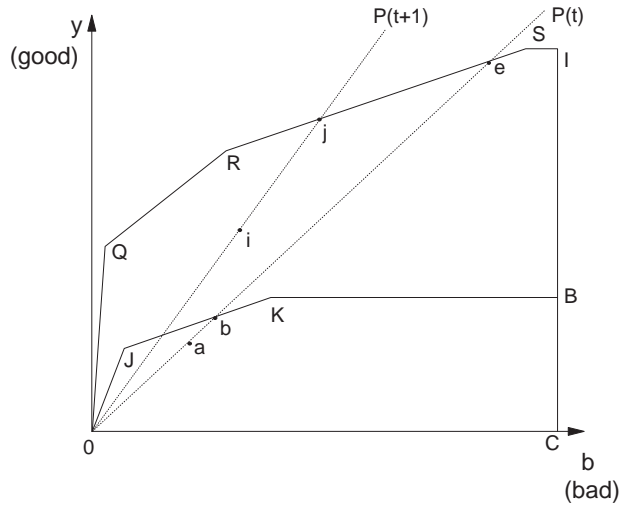


Fig. 2. Regulated frontiers in periods t and $t+1$.

decreased bad output production is associated with that component. A value of unity indicates no change in bad output production is associated with that component.

Improved TE is associated with increased bad output production, while decreased TE is associated with reduced bad output production. Technical improvement (deterioration) is associated with increased (decreased) bad output production. Likewise, an increase (decrease) in IG is associated with an increase (decrease) in bad output production. Combining the TC and IG components yields a measure that is comparable to the industry output component of the SDA model, and it is also comparable to the combined effect of the GDP and industry share of GDP components of the ID model. All of the changes in bad output production associated with TE, TC, and IG assume a constant output mix is maintained. The OM effect, which is comparable to the emission intensity component of the ID and SDA studies, reflects movements along the production frontier that may be associated with regulatory induced technical change. Shifting to a process that produces reduced (increased) quantities of the bad output per unit of the good output is associated with decreased (increased) bad output production.

An important issue is the characterization of technical change. When modeling the joint production of good and bad outputs, there are several definitions of technical change. One definition holds TC measures production frontier shifts while a producer is credited for simultaneously expanding production of the good output and contracting production of the bad output (see Färe et al., 2001). This definition of technical change results in combining the shift in the frontier (TC) and movements along the frontier (OM) components from this study. Another definition of TC credits a producer for a simultaneous proportional expansion of both good and bad outputs. The advantage of this definition is that it allows for the calculation of separate TC and OM effects. Because the ID and SDA decomposition models assume that any change in output of the entire economy results in proportional changes in the outputs of all sectors and the fuel consumption of all sectors, employing the second definition of technical change is consistent with the perspective of the ID and SDA decomposition methods. Therefore, the second definition of TC is adopted in order to make the results of this study more comparable to the ID and SDA methods.

The index of change in bad output production associated with changes in TE is calculated in the same manner as Färe et al. (1994b) and Li and Chan (1998). The observed production of

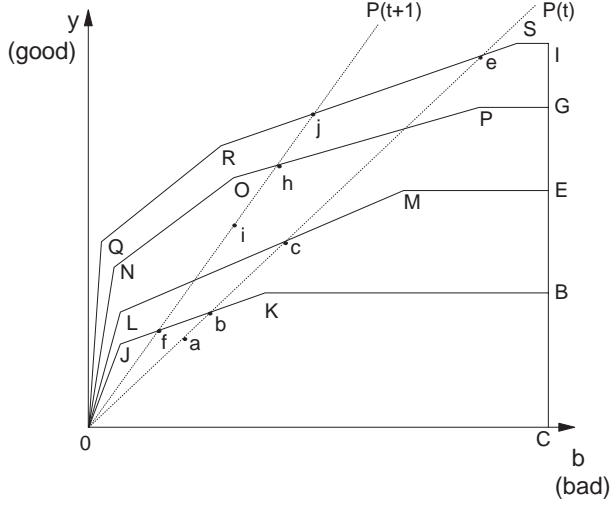


Fig. 3. Decomposition of bad output production.

output in periods t and $t+1$ are radially projected to points on the regulated frontiers for periods t and $t+1$, respectively. The index of change in bad output production associated with TC also follows [Färe et al. \(1994b\)](#) and [Li and Chan \(1998\)](#). When using the period $t+1$ input and output mix, the change in bad output production associated with TC is the ratio of the distance function using the technology of period t to the distance function using the period $t+1$ technology. This same procedure is followed with the period t input vector and output mix.

The index of change in bad output production associated with IG follows [Li and Chan \(1998\)](#). When using the period $t+1$ technology and period t output mix, the change in bad output production associated with IG is the ratio of the distance function with the period t input vector to the distance function with the period $t+1$ input vector. The same procedure is followed for the case with the period t technology and period $t+1$ output mix. Because the input vector, x , consists of fuel and non-fuel inputs, the IG component of (9) can be rewritten as:

$$\begin{aligned}
 IG_t^{t+1} = & \left[\left(\frac{D_{or}^{t+1}(x_{nf}^t, x_f^t, y^t, b^t)}{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^{t+1}, y^t, b^t)} \right) \left(\frac{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^t, y^t, b^t)}{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^{t+1}, y^t, b^t)} \right) \right]^{1/2} \\
 & \times \left[\left(\frac{D_{or}^t(x_{nf}^t, x_f^t, y^{t+1}, b^{t+1})}{D_{or}^t(x_{nf}^{t+1}, x_f^t, y^{t+1}, b^{t+1})} \right) \left(\frac{D_{or}^t(x_{nf}^{t+1}, x_f^t, y^{t+1}, b^{t+1})}{D_{or}^t(x_{nf}^{t+1}, x_f^{t+1}, y^{t+1}, b^{t+1})} \right) \right]^{1/2} \quad (11)
 \end{aligned}$$

where x_{nf} represents non-fuel inputs and x_f represents fuel inputs. The terms in (11) can be rewritten as:

$$\begin{aligned}
 IG_t^{t+1} = & \left[\left(\frac{D_{or}^{t+1}(x_{nf}^t, x_f^t, y^t, b^t)}{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^t, y^t, b^t)} \right) \left(\frac{D_{or}^t(x_{nf}^t, x_f^t, y^{t+1}, b^{t+1})}{D_{or}^t(x_{nf}^{t+1}, x_f^t, y^{t+1}, b^{t+1})} \right) \right]^{1/2} \\
 & \times \left[\left(\frac{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^t, y^t, b^t)}{D_{or}^{t+1}(x_{nf}^{t+1}, x_f^{t+1}, y^t, b^t)} \right) \left(\frac{D_{or}^t(x_{nf}^{t+1}, x_f^t, y^{t+1}, b^{t+1})}{D_{or}^t(x_{nf}^{t+1}, x_f^{t+1}, y^{t+1}, b^{t+1})} \right) \right]^{1/2} \quad (12)
 \end{aligned}$$

The expression in the first set of brackets of Eq. (12) represents the index of change in bad output production associated with changes in non-fuel inputs, IG_NF, (i.e., capital and labor) while the expression in the second set of brackets denotes the index of change in bad output production associated with fuel consumption, IG_F (coal, oil, and natural gas).

The final factor, which is the change in the mix of good and bad outputs, represents a direct effect of changes in the intensity of pollution abatement activities.¹² For a given input vector, reallocating resources from good output production to pollution abatement activities appears as a counterclockwise movement along the production frontier. In Eq. (9), the four distance functions associated with the OM effect scale observed bad output production to one of two production frontiers. These ratios represent the theoretical maximum bad output production given the different combinations of technology, inputs, and output mix. For example, $b_i^{t+1}/D_{or}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})$ scales b_i^{t+1} to the frontier consisting of the technology and inputs of period $t+1$, while $b_i^t/D_{or}^{t+1}(x^{t+1}, y^t, b^t)$ scales b_i^t to the same frontier. However, the first ratio maintains the output mix of period $t+1$, while the second ratio maintains the output mix of period t . These two points on the frontier allow a measurement of changes in production of the i th bad output associated with movements along the production frontier produced by the technology and inputs of period $t+1$.

To illustrate the previous discussion, Fig. 3 extends Fig. 2 by introducing two additional production frontiers. Frontier 0NOPGC depicts combinations of good and bad outputs produced by period $t+1$ inputs and the period t technology, while frontier 0LMEC represents combinations of good and bad outputs produced by period t inputs using the period $t+1$ technology. The positions of frontiers 0LMEC and 0NOPGC may be reversed and may intersect.

In Fig. 3, ΔEMIT_i can be written as:

$$\Delta\text{EMIT}_i = \left(\frac{0i}{0a} \right) = \left[\frac{0i/0j}{0a/0b} \right] \left[\left(\frac{0a/0b}{0a/0c} \right) \left(\frac{0i/0h}{0i/0j} \right) \right]^{1/2} \left[\left(\frac{0a/0c}{0a/0e} \right) \left(\frac{0i/0f}{0i/0h} \right) \right]^{1/2} \\ \times \left[\left(\frac{0i}{0a/0e} \right) \left(\frac{0i}{0a/0b} \right) \right]^{1/2} \quad (13)$$

which corresponds to Eq. (9). Eq. (13) can be rewritten as:

$$\Delta\text{EMIT}_i = \left(\frac{0i}{0a} \right) = \left[\left(\frac{0i}{0j} \right) \left(\frac{0b}{0a} \right) \right] \left[\left(\frac{0c}{0b} \right) \left(\frac{0j}{0h} \right) \right]^{1/2} \\ \times \left[\left(\frac{0e}{0c} \right) \left(\frac{0h}{0f} \right) \right]^{1/2} \left[\left(\frac{0j}{0e} \right) \left(\frac{0f}{0b} \right) \right]^{1/2} \quad (14)$$

In Fig. 3, the expression in the first set of brackets represents the index of change in bad output production associated with TE, the expression in the second set of brackets is the index of the change in bad output production associated with TC, the expression in the third set of brackets is the index of the change in bad output production associated with IG, while the expression in the fourth set of brackets is the index of change in bad output production associated with OM.

Since distance functions can be calculated as solutions to linear programming (LP) problems, the next step is specifying the distance functions in terms of LP problems. The LP problems

¹² Lovell (2003) discusses alternative approaches to modeling the output mix effect.

associated with $D_{or}^t(x^t, y^t, b^t)$ and $D_{or}^{t+1}(x^t, y^t, b^t)$ are used to illustrate their application.¹³ The two LP problems specified to calculate the change in bad output production associated with changes in TE are solved using observations from the same period. First, the TE of producer k' in period t using the regulated technology from period t is:

$$\begin{aligned}
 (D_{or}^t(x^{t,k'}, y^{t,k'}, b^{t,k'}))^{-1} &= \max \beta \\
 \text{s.t. } \sum_{k=1}^K z_k y_{km}^t &\geq \beta y_{k'm}^t \quad m = 1, \dots, G \\
 \sum_{k=1}^K z_k b_{ki}^t &= \beta b_{k'i}^t \quad i = 1, \dots, B \\
 \sum_{k=1}^K z_k x_{kn}^t &\leq x_{k'n}^t \quad n = 1, \dots, N \\
 z_k &\geq 0 \quad k = 1, \dots, K
 \end{aligned} \tag{15}$$

The objective function, β , represents the maximum proportional expansion of the output vectors for a given technology, input vector, and output mix. In Fig. 2, Eq. (15) calculates the value $0b/0a$.¹⁴ The constraints are interpreted in the same manner as the constraints for Eq. (1). Determining the index of change in bad output production associated with changes in TE also requires solving the LP problem associated with $D_{or}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})$.

The index of change in bad output production associated with TC is determined by two pairs of LP problems. The following mixed-period LP problem maximizes the value of the distance function for producer k' from period t using the period $t+1$ regulated technology:

$$\begin{aligned}
 (D_{or}^{t+1}(x^{t,k'}, y^{t,k'}, b^{t,k'}))^{-1} &= \max \beta \\
 \text{s.t. } \sum_{k=1}^K z_k y_{km}^{t+1} &\geq \beta y_{k'm}^t \quad m = 1, \dots, M \\
 \sum_{k=1}^K z_k b_{ki}^{t+1} &= \beta b_{k'i}^t \quad i = 1, \dots, B \\
 \sum_{k=1}^K z_k x_{kn}^{t+1} &\leq x_{k'n}^t \quad n = 1, \dots, N \\
 z_k &\geq 0 \quad k = 1, \dots, K
 \end{aligned} \tag{16}$$

¹³ A formal statement of the output correspondence for the regulated and unregulated frontiers is in Färe and Grosskopf (1983) and Färe et al. (1986, p. 170).

¹⁴ The β in the LP problem is the reciprocal of θ in the distance function equation.

In Fig. 2, Eq. (16) calculates the distance $0c/0a$. The reference technology relative to which (x^t, y^t) is evaluated consists of observations from period $t+1$. The ratio of $D_{or}^t(x^t, y^t, b^t)$, Eq. (15), and $D_{or}^{t+1}(x^t, y^t, b^t)$ yields $0c/0b$. This is one of two ratios required to calculate the index of change in bad output production associated with TC.

4. Data and results

This section discusses the data used to implement the joint production decomposition model and the empirical results. Data from coal-fired power plants from 1985 to 1995 are used to solve the LP problems. The technology modeled in this study consists of one good output, “net electrical generation” (kWh), and two bad outputs—sulfur dioxide (SO₂) and nitrogen oxides (NO_x). The inputs consist of the capital stock, the number of employees, and the heat content (in Btu) of coal, oil, and natural gas consumed at each power plant (there are separate constraints for each of the fuels). While the power plants may consume coal, oil, or natural gas, in order to model a homogeneous production technology, coal must provide at least 95% of the Btu of fuels consumed by each plant.¹⁵ The U.S. Federal Energy Regulatory Commission (FERC) Form 1 survey (U.S. FERC, various years) collects information on the cost of plant and equipment and the average number of employees for each power plant.¹⁶ The U.S. Department of Energy’s (DOE) Form EIA-767 survey (see U.S. Department of Energy, various years) is the source of information about fuel consumption and net generation of electricity, which is used by the DOE to derive its estimates of SO₂ and NO_x emissions. The sample consists of 92 power plants for each year from 1985 to 1995. “Windows” are used when modeling the production technology which means the period $t+1$ technology consists of observations from periods $t+1$, t , and $t-1$, while the period t technology consists of observations from periods t , $t-1$, and $t-2$. As a result, there are eight two year-pairs from 1987–88 to 1994–1995 associated with each power plant. Table 1 presents summary statistics of the data for 1987 and 1995.¹⁷

Table 2 presents the results for each power plant in the sample.¹⁸ Δ EMIT, which is estimated by Eq. (6), is the geometric mean of the annual index of change in the SO₂ and NO_x emissions.

¹⁵ A number of plants consume fuels other than coal, oil, and natural gas (e.g., petroleum coke, blast furnace gas, coal–oil mixture, fuel oil #2, methanol, propane, wood and wood waste, and refuse, bagasse and other nonwood waste). In this study, any plant whose consumption of fuels other than coal, oil, and natural gas represented more than 0.0001% of its total fuel consumption (in Btu) is excluded. I ignore consumption of fuels other than coal, oil, and natural gas when these fuels represent less than 0.0001% of a plants fuel consumption.

¹⁶ The FERC 1 survey only collects data on the historical cost of plant and equipment—no data are collected on investment expenditures. Hence, changes in the value of plant and equipment reflect the value of additional plant and equipment minus the value of retired plant and equipment. For this study, I assume changes in cost of P&E reflect net investment (NI), which is the same assumption employed by Yaisawarng and Klein (1994, p. 453, Footnote 30) and Carlson et al. (2000, p. 1322). I then convert the historical cost of plant data to constant dollar values using the Handy–Whitman Index (HWI) (see Whitman, Requardt and Associates, LLP, 2002). 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.

¹⁷ An appendix contains a detailed discussion of the data. The LP problems are estimated using GAMS/MINOS. The appendix, data, and GAMS program are available from the author upon request.

¹⁸ Subtracting unity from the values reported in Table 2 and multiplying by 100 provides the average annual percentage change of the component.

Table 1
Summary statistics for 92 coal-fired power plants: 1987 and 1995

	Units	Mean	S.D.	Maximum	Minimum
<i>1987</i>					
Electricity	kWh (millions)	4314.2	3526.2	14,598.6	45.4
SO ₂	Short tons	55,287.4	70,301.0	367,330.4	704.2
NO _x	Short tons	18,241.7	15,727.6	68,829.2	243.9
Capital stock	Dollars (in millions, 1973\$)	216.4	127.6	568.2	38.1
Employees	Workers	219.0	138.5	687.0	37.0
Heat content of coal	Btu (in billions)	43,887.9	35,456.2	160,037.4	683.8
Heat content of oil	Btu (in billions)	101.5	107.9	432.4	0.0
Heat content of gas	Btu (in billions)	51.5	189.6	1267.7	0.0
<i>1995</i>					
Electricity	kWh (in millions)	4686.5	4065.3	18,212.1	166.6
SO ₂	Short tons	40,745.2	48,244.8	252,344.6	1,293.2
NO _x	Short tons	17,494.0	16,190.1	72,524.1	423.1
Capital stock	Dollars (in millions, 1973\$)	240.0	146.4	750.0	39.3
Employees	Workers	185.2	110.9	535.0	39.0
Heat content of coal	Btu (in billions)	46,936.3	39,852.6	173,436.8	1,869.3
Heat content of oil	Btu (in billions)	91.5	112.7	618.9	0.0
Heat content of gas	Btu (in billions)	76.5	275.5	2083.0	0.0

TE, TC, IG, and OM are estimated by components of Eq. (9), while IG_F and IG_NF are components of Eq. (12).

Geometric means of the eight two-year periods are reported for each power plant. For all 92 power plants, the annual change in ΔEMIT for SO₂ emissions ranges from a 29.76% annual decrease for Montrose (ID 2080) to an annual increase of 31.95% for Mill Creek (ID 1364), while the annual change in ΔEMIT for NO_x emissions ranges from an annual decrease of 15.62% for R.P. Smith (ID 1570) to a 30.99% annual increase for Hoot Lake (ID 1943). If only the 72 power plants for which all LP programs are feasible are considered, the annual change in ΔEMIT for SO₂ emissions ranges from a decrease of 24.65% for General James M. Gavin (ID 8102) to an annual increase of 18.13% for James H. Miller Jr. (ID 6002).

The remaining discussion refers to only those power plants for which all LP problems are feasible. The geometric means at the bottom of each column are for the 72 power plants with no infeasible LP problems.¹⁹ Between 1987 and 1995, SO₂ emissions declined at an annual rate of 3.81%, while NO_x emissions declined at an annual rate of 1.00%. TC is associated with annual increases in SO₂ and NO_x emissions of 3.35%. IG is associated with annual decreases in emissions of 1.44%, of which fuel consumption (IG_F) is associated with annual decreases in SO₂ and NO_x emissions of 1.12%. OM is associated with annual declines in SO₂ emissions of 4.87%, while OM is associated with a 2.10% annual decrease in NO_x emissions.

Annual changes in emissions associated with TE ranged from an annual decrease of 4.85% for Yates (ID 728) to a 4.13% annual increase for Hoot Lake (ID 1943), while the TC

¹⁹ The cause of the infeasible LP problems is the assumption of weak disposability that is imposed on bad outputs. In some of the mixed-period LP problems, the output set (i.e. production frontier) is determined by observations from period t ; however, observations from both t and $t+1$ are in the LP problem. As is the case for the Malmquist–Luenberger productivity index (see Färe et al., 2001), some of these mixed-period LP problems may be infeasible. For example, $D_{\text{or}}^t(x^{t+1}, y^{t+1}, b^{t+1})$ may contain observations for which $(y^{t+1}, b^{t+1}) \notin S_t^t(x^{t+1})$.

Table 2

Geometric means of eight 2-year periods between 1987 and 1995

Plant name	Plant ID	Δ EMIT (SO ₂)	Δ EMIT (NO _x)	TE	TC	IG	IG_NF	IG_F	OM (SO ₂)	OM (NO _x)
Barry	3	1.0248	1.0111	0.9918	1.0149	1.0068	0.9992	1.0076	1.0112	0.9977
Gorgas	8	1.0913	1.0259	1.0069	1.0055	1.0238	1.0000	1.0238	1.0528	0.9898
Comanche	470	1.0224	1.0289	1.0065	1.1195	0.9178	0.9946	0.9228	0.9886	0.9948
Brandon Shores	602	1.1094	1.1168	1.0016	1.0079	1.1106	0.9972	1.1137	0.9895	0.9961
Crist	641	0.8273	0.9180	0.9708	1.0220	0.9558	0.9999	0.9559	0.8724	0.9681
Hammond	708	0.8546	0.8971	0.9747	1.0218	0.9201	1.0000	0.9201	0.9326	0.9790
Harlee Branch	709	0.9681	0.9865	0.9990	0.9978	0.9876	0.9964	0.9912	0.9834	1.0022
Yates	728	0.7922	0.8632	0.9515	1.0221	0.9016	1.0002	0.9014	0.9035	0.9845
E.D. Edwards	856	1.0624	0.9776	0.9857	1.0136	1.0071	1.0000	1.0071	1.0560	0.9717
Coffeeen	861	0.8423	1.0049	1.0000	1.0237	0.9969	0.9978	0.9991	0.8253	0.9847
Grand Tower	862	0.9827	0.9952	0.9882	1.0037	0.9939	1.0000	0.9939	0.9969	1.0096
Hutsonville	863	0.9254	0.9315	0.9879	1.0434	0.8981	1.0000	0.8981	0.9996	1.0061
Meredosia	864	0.9668	0.9867							
Kincaid	876	0.7544	0.9574	1.0000	1.1217	0.9706	0.9792	0.9913	0.6929	0.8794
Powerton	879	0.9597	1.0010	0.9938	1.2334	0.9550	0.9962	0.9586	0.8199	0.8552
Joppa Steam	887	0.8833	1.0684	1.0012	1.0153	1.0626	0.9994	1.0632	0.8178	0.9891
Baldwin	889	1.0023	0.9926	1.0009	1.0132	0.9838	0.9926	0.9912	1.0047	0.9949
Clifty Creek	983	0.8753	1.0115	1.0000	1.0632	1.0138	0.9975	1.0163	0.8121	0.9385
Tanners Creek	988	0.9615	1.0356	0.9891	1.0099	1.0419	1.0006	1.0413	0.9239	0.9950
H.T. Pritchard	991	0.9445	0.9973	0.9701	1.0204	1.0224	1.0000	1.0224	0.9333	0.9854
Petersburgh	994	1.0357	0.9957	0.9990	1.0287	1.0042	0.9998	1.0044	1.0036	0.9648
Edwardsport	1004	1.0051	1.0108	0.9887	1.0012	1.0124	1.0000	1.0124	1.0029	1.0086
R. Gallagher	1008	0.9663	0.9825	0.9877	1.0103	1.0360	0.9998	1.0363	0.9347	0.9504
F.B. Culley	1012	0.8094	1.0110	1.0050	1.0370	0.8987	1.0065	0.8928	0.8642	1.0795
Lansing	1047	0.9898	0.9344	0.9686	1.0053	0.9739	0.9962	0.9776	1.0437	0.9852
Lawrence	1250	0.9332	1.0030							
E.W. Brown	1355	0.8828	0.9081	0.9700	1.0314	0.9450	1.0008	0.9443	0.9337	0.9605
Ghent	1356	0.9345	1.0103	0.9999	1.0087	1.0436	1.0017	1.0418	0.8878	0.9598
Green River	1357	0.9663	0.9490	0.9933	1.0065	0.9602	1.0000	0.9602	1.0066	0.9886
Mill Creek	1364	1.3195	0.9875							
R.P. Smith	1570	0.8779	0.8438	0.9940	1.0317	0.8690	1.0000	0.8690	0.9852	0.9469
Mount Tom	1606	0.9468	0.9416							
B.C. Cobb	1695	0.9719	1.0099	0.9778	1.0185	0.9924	1.0000	0.9924	0.9835	1.0219
Trenton Channel	1745	0.9856	1.0266	0.9684	1.0238	1.0007	0.9999	1.0008	0.9934	1.0348
Hoot Lake	1943	1.0920	1.3099	1.0413	1.0020	1.2654	1.0000	1.2654	0.8272	0.9922
Montrose	2080	0.7024	0.9479							
Labadie	2103	0.8928	0.9851	0.9792	1.0094	1.0002	0.9955	1.0047	0.9032	0.9965
Sioux	2107	0.9222	0.9334	0.9753	1.0127	0.9879	0.9986	0.9893	0.9452	0.9567
Goudey	2526	0.9570	0.9251	1.0192	0.9966	0.9485	1.0000	0.9485	0.9935	0.9604
Greenidge	2527	0.9785	0.9523	1.0098	1.0092	0.9748	1.0000	0.9748	0.9850	0.9586
Milliken	2535	0.8657	0.9843	0.9804	1.0461	0.9945	1.0012	0.9933	0.8488	0.9651
C.R. Huntley	2549	0.9750	0.9904							
Dunkirk	2554	0.9947	0.9566							
Rochester	2642	1.0041	1.0049	0.9825	1.0142	1.0054	1.0000	1.0054	1.0023	1.0030
Asheville	2706	1.0125	1.0169	1.0005	1.0049	1.0127	1.0000	1.0127	0.9944	0.9987
G.G. Allen	2718	1.0542	1.0363							
Cliffside	2721	0.9871	0.9560							
Marshall	2727	1.0513	1.0009							
R.M. Heskett	2790	0.8827	0.9329							
J.M. Stuart	2850	0.9326	0.9833	0.9926	0.9982	1.0083	1.0004	1.0079	0.9335	0.9842
R.E. Burger	2864	0.9397	0.9426	1.0018	1.0295	0.9296	0.9723	0.9561	0.9802	0.9832

Table 2 (continued)

Plant name	Plant ID	Δ EMIT (SO ₂)	Δ EMIT (NO _x)	TE	TC	IG	IG_NF	IG_F	OM (SO ₂)	OM (NO _x)
Muskingum River	2872	0.8813	0.9285	0.9825	1.0093	0.9446	0.9939	0.9504	0.9410	0.9914
Kyger Creek	2876	0.8979	0.9956	1.0011	1.0409	0.9771	0.9997	0.9774	0.8819	0.9779
Elrama	3098	1.0718	1.0114							
Seward	3130	0.9882	0.9658	0.9855	1.0167	0.9923	0.9992	0.9930	0.9940	0.9714
Shawville	3131	0.9960	0.9602	0.9982	1.0044	1.0033	0.9991	1.0042	0.9901	0.9544
New Castle	3138	0.9702	0.9637	0.9925	1.0122	0.9652	0.9998	0.9655	1.0006	0.9939
Brunner Island	3140	0.9628	0.9319							
Montour	3149	1.0298	0.9473							
Armstrong	3178	0.9371	0.9009	1.0134	1.0166	0.9194	1.0000	0.9194	0.9894	0.9511
Watertree	3297	1.0024	1.0080	0.9997	1.0019	1.0076	1.0001	1.0075	0.9932	0.9988
Big Brown	3497	0.9887	0.9885	0.9958	1.0374	0.9471	0.9708	0.9756	1.0105	1.0103
Carbon	3644	1.0538	1.0627	1.0003	1.0444	1.0224	0.9991	1.0233	0.9865	0.9949
Clinch River	3775	1.0313	1.0343	0.9918	1.0118	1.0272	0.9992	1.0280	1.0005	1.0034
Glen Lyn	3776	1.0582	1.0163	1.0184	1.0297	1.0626	0.9997	1.0630	0.9496	0.9121
Potomac River	3788	0.9968	0.9982	0.9711	1.0296	0.9994	1.0000	0.9994	0.9976	0.9990
Bremo	3796	1.0335	0.9976	0.9835	1.0161	0.9898	1.0000	0.9898	1.0449	1.0086
Kanawha River	3936	0.9708	0.9735	0.9735	1.0191	0.9817	1.0000	0.9817	0.9968	0.9996
Rivesville	3945	0.8818	0.8732	0.9790	1.0102	0.8793	1.0000	0.8793	1.0141	1.0042
Willow Island	3946	0.9894	0.9789	1.0096	1.0181	0.9519	1.0000	0.9519	1.0112	1.0006
Kammer	3947	0.9748	1.0008	0.9975	1.0180	0.9913	0.9950	0.9963	0.9684	0.9942
Mitchell	3948	0.9879	0.9942	0.9955	1.0070	1.0436	0.9999	1.0437	0.9442	0.9502
Nelson Dewey	4054	0.8883	0.9367							
Pulliam	4072	0.7859	1.0470							
Dave Johnston	4158	1.0133	1.0672	1.0188	1.0845	0.9937	0.9956	0.9981	0.9229	0.9720
Naughton	4162	1.0500	1.0256	0.9979	1.0021	1.0168	1.0001	1.0167	1.0326	1.0086
James H. Miller Jr.	6002	1.1813	1.1886	0.9935	1.0633	1.1036	0.9970	1.1069	1.0132	1.0194
Pleasants	6004	1.2676	0.9846							
Duck Creek	6016	0.9880	1.0064	0.9868	1.0187	1.0065	1.0000	1.0065	0.9765	0.9947
Newton	6017	1.0830	1.0334							
Sooner	6095	1.0263	1.0253	1.0075	1.0572	1.0045	0.9512	1.0559	0.9592	0.9582
Welsh	6139	0.9793	0.9597	1.0007	1.0599	0.9779	0.9933	0.9845	0.9442	0.9254
Martin Lake	6146	1.0906	1.0061	0.9837	1.0790	0.9274	0.9851	0.9414	1.1079	1.0221
Monticello	6147	0.9586	0.9803	0.9846	1.0000	0.9803	1.0049	0.9755	0.9932	1.0156
Rush Island	6155	0.9298	0.9879	0.9862	1.0056	1.0231	1.0000	1.0231	0.9164	0.9735
Coleto Creek	6178	1.0066	0.9615							
Harrington	6193	0.9921	0.9892	1.0000	1.5185	0.8868	0.9929	0.8931	0.7368	0.7346
Pawnee	6248	1.0485	0.9972	1.0012	1.0930	0.8951	0.9883	0.9057	1.0704	1.0181
Mountaineer	6264	0.9526	0.9648	0.9806	1.0186	0.9630	0.9997	0.9633	0.9904	1.0030
Belews Creek	8042	0.9960	1.0314	1.0007	1.0448	1.0038	0.9886	1.0154	0.9491	0.9828
General James M. Gavin	8102	0.7535	1.0103	1.0000	1.0571	0.9581	0.9929	0.9649	0.7439	0.9976
Cheswick	8226	1.0101	0.9529							
Geometric mean of 72 plants with no infeasible LP		0.9619	0.9900	0.9928	1.0335	0.9856	0.9968	0.9888	0.9513	0.9790

A blank cell indicates at least one infeasible LP problem.

effect ranged from an annual decrease of 0.34% for Goudey (ID 2526) to a 51.85% annual increase for Harrington (ID 6193). Changes in emissions associated with IG ranged from an annual decrease of 13.10% for R.P. Smith (ID 1570) to an annual increase of 26.54% for Hoot Lake (ID 1943). Changes in emissions associated with non-fuel inputs ranged from an annual decrease of 4.88% for Sooner (ID 6095) to an annual increase of 0.65% for F.B. Culley (ID

Table 3

Geometric means of annual changes for each 2-year period between 1987 and 1995 (72 electric power plants with no infeasible LP problems)

Two-year pairs	Δ EMIT (SO ₂)	Δ EMIT (NO _x)	TE	TC	IG	IG_NF	IG_F	OM (SO ₂)	OM (NO _x)
1987–1988	1.0523	1.0641	1.0093	1.0055	1.0499	0.9959	1.0543	0.9876	0.9987
1988–1989	1.0368	1.0507	1.0029	1.0150	1.0417	0.9976	1.0442	0.9777	0.9909
1989–1990	0.9511	0.9455	1.0002	1.0293	0.9375	1.0000	0.9375	0.9854	0.9796
1990–1991	0.9257	0.9500	0.9982	1.0345	0.9300	0.9997	0.9302	0.9640	0.9893
1991–1992	0.9783	0.9653	1.0023	1.0286	0.9619	0.9959	0.9659	0.9865	0.9734
1992–1993	1.0197	1.0313	1.0011	1.0270	1.0366	0.9997	1.0369	0.9567	0.9676
1993–1994	0.9617	0.9390	0.9985	1.0196	0.9621	0.9957	0.9662	0.9819	0.9587
1994–1995	0.7957	0.9827	0.9319	1.1123	0.9732	0.9895	0.9835	0.7888	0.9742
Geometric means	0.9619	0.9900	0.9928	1.0335	0.9856	0.9968	0.9888	0.9513	0.9790

1012), while changes in emissions associated with fuel consumption ranged from an annual decline of 13.10% for R.P. Smith (ID 1570) to an annual increase of 26.54% for Hoot Lake (ID 1943).

The only difference when decomposing the factors associated with changes in SO₂ and NO_x is associated with changes associated with the output mix (OM). Changes in SO₂ emissions associated with changes in quantity of SO₂ produced per unit of the good output ranges from an annual decrease of 30.71% for Kincaid (ID 876) to an annual increase of 10.79% for Martin Lake (ID 6146). Changes in NO_x emissions associated with changes in the quantity of NO_x produced per unit of the good output ranges from an annual decrease of 26.54% for Harrington (ID 6193) to an annual increase of 7.95% for F.B. Culley (ID 1012).

Table 3 provides insights into trends over the eight two-year periods. The largest increase in SO₂ emissions was a 5.23% increase between 1987 and 1988, while the largest decrease was a 20.43% reduction during 1994–95. The steepest increase in NO_x emissions was 6.41% during 1987–88, while the steepest decline 6.1% during 1993–94. For both SO₂ and NO_x, increased fuel consumption was the factor most closely associated with the 1987–88 increase in emissions, while output mix changes was most closely associated with the 1993–94 decline in NO_x emissions and 1994–95 decline in SO₂ emissions.

Environmental regulations require producers to undertake pollution abatement activities whose output is reduced bad output production. From the perspective of the joint production model, the direct effects of environmental regulations are changes in bad output production associated with changes in the OM. While changing to a process that produces less of the bad output per unit of the good output is a direct effect of environmental regulations, these regulations also indirectly affect bad output production. For example, increased regulatory stringency can reduce input use by an industry which can result in reduced bad output production as resources are shifted among industries in response to changing environmental regulations. Because this study—like previous decomposition studies—does not calculate the effect of pollution abatement activities on technical change, changes in technical efficiency, or changes in input growth, it does not determine the total effect of pollution abatement activities on bad output production.

5. Conclusions

The methodology presented in this study offers an alternative to the ID and SDA techniques that have been used in previous studies of the relative importance of factors associated with

changes in emissions. In order to determine the relative importance of changes in technical efficiency, technical change, changes in the output mix, and input growth on the emissions of power plants in the United States between 1987 and 1995, a joint production model was specified. Caution must be exercised when interpreting the results, which are influenced by the number of inputs and bad outputs specified in the production technology. Nevertheless, the results provide evidence that between 1987 and 1995 technical change is associated with increased NO_x and SO_2 emissions. Changes in technical efficiency and changes in non-fuel inputs are associated with small decreases in bad output production. While changes in fuel consumption is almost as important as changes in the output mix in explaining declining production of NO_x emissions, changes in the output mix is clearly the most important factor associated with the reduced production of SO_2 emissions.

Using only period $t+1$ as the reference technology for mixed-period LP problems and assuming a sequential production technology in which the frontier of period $t+1$ is constructed from period $t+1$ observations and all previous periods (see Shestalova, 2003; Pasurka, 2003) would ensure that all LP problems were feasible. However, a drawback to this approach is that using period t as the reference technology is likely to produce different results than those found using period $t+1$. These differences represent the justification for using a geometric mean of the results for the two reference technologies. Obviously, the drawback to employing period t as a reference technology in a mixed-period LP problem is the possibility of infeasible LP problems. Extending the analysis from the “windowed” frontiers used in this study to sequential frontiers might help reduce the incidence of infeasible LP problems.

There are several additional avenues of future exploration using the decomposition framework specified in this study. Changes in bad output production associated with the IG_F component can be further decomposed into the changes in production of the bad output associated with changes in the fuel mix (i.e., the relative growth rates of different fuel types).²⁰ This extension would allow the joint production model to more closely emulate the SDA and ID models. The decomposition framework developed in this study could also be applied to analyses of changes in CO_2 emissions. Finally, instead of assuming a piecewise-linear production technology, an exploration of the consequences of specifying a parametric joint production technology on the decomposition analysis might yield additional insights.

References

- Aiken, Deborah Vaughn, Pasurka, Carl A., 2002. Sources of emission changes: a joint production perspective of existing decomposition models. Presented at the Fourteenth International Conference on Input–Output Techniques, Université du Québec à Montréal, Canada.
- Ang, Beng Wah, 1999. Decomposition methodology in energy demand and environmental analysis. In: van den Bergh, Jeroen C.J.M. (Ed.), *Handbook of Environmental and Resource Economics*. Edward Elgar, Northampton, MA, pp. 1146–1163.
- Ang, Beng Wah, Zhang, F.Q., 2000. A survey of index decomposition analysis in energy and environmental studies. *Energy—The International Journal* 25, 1149–1176.
- Bruvoll, Annegrete, Medin, Hege, 2003. Factors behind the environmental Kuznets curve: a decomposition of the changes in air pollution. *Environmental and Resource Economics* 24, 27–48.
- Carlson, Curtis, Burtraw, Dallas, Cropper, Maureen, Palmer, Karen, 2000. Sulfur dioxide control by electric utilities: what are the gains from trade? *Journal of Political Economy* 108, 1292–1326.

²⁰ Since coal is the dominant fuel among the electric utility plants sampled for this study, disaggregating the fuel consumption component into changes in fuel mix was not undertaken based on the belief that it was unlikely to produce any useful insights.

- Cherp, Aleg, Kopteva, Irina, Mnatsakanian, Ruben, 2003. Economic transition and environmental sustainability: effects of economic restructuring on air pollution in the Russian Federation. *Journal of Environmental Management* 68, 141–151.
- Färe, Rolf, Grosskopf, Shawna, 1983. Measuring output efficiency. *European Journal of Operational Research* 13, 173–179.
- Färe, Rolf, Grosskopf, Shawna, Pasurka, Carl, 1986. Effects on relative efficiency in electric power generation due to environmental controls. *Resources and Energy* 8, 167–184.
- Färe, Rolf, Grosskopf, Shawna, Lovell, C.A. Knox, Pasurka, Carl, 1989. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *Review of Economics and Statistics* 71, 90–98.
- Färe, Rolf, Grosskopf, Shawna, Lovell, C.A. Knox, 1994a. *Production Frontiers*. Cambridge University Press, Cambridge.
- Färe, Rolf, Grosskopf, Shawna, Norris, Mary, Zhang, Zhongyang, 1994b. Productivity growth, technical progress and efficiency change in industrialized countries. *American Economic Review* 84, 66–83.
- Färe, Rolf, Grosskopf, Shawna, Pasurka, Carl, 2001. Accounting for air pollution emissions in measures of state manufacturing productivity growth. *Journal of Regional Science* (3), 381–409.
- Grosskopf, Shawna, 2003. Some remarks on productivity and its decompositions. *Journal of Productivity Analysis* 20, 459–474.
- Hammer, Henrik, Löfgren, Åsa, 2001. The determinants of sulfur emissions from oil consumption in Swedish manufacturing industries. *The Energy Journal* 22, 107–126.
- Hoekstra, Rutger, van der Bergh, Jeroen J.C.J.M., 2003. Comparing structural and index decomposition analysis. *Energy Economics* 25, 39–64.
- Leontief, Wassily, Ford, Daniel, 1972. Air pollution and the economic structure: empirical results of input–output computations. In: Bródy, A., Carter, A.P. (Eds.), *Input–Output Techniques*. North-Holland Publishing Co., Amsterdam, pp. 9–29.
- Li, Sung Ko, Chan, Hing Lin, 1998. Decomposing output growth in the presence of multiple outputs. Presented at the University of Georgia Productivity Workshop.
- Lin, Sue J., Chang, Tzu C., 1996. Decomposition of SO₂, NO_x, and CO₂ emissions from energy use of major economic sectors in Taiwan. *The Energy Journal* 17, 1–17.
- Lovell, C.A. Knox, 2003. The decomposition of Malmquist productivity indexes. *Journal of Productivity Analysis* 20, 437–458.
- Meyer, Helmut, Carsten Stahmer, 1989, “Energy consumption and sulfur dioxide emissions and the Federal Republic of Germany in 1980 and 1986,” Ninth International Conference on Input–Output Techniques, Keszthely, Hungary, Sept. 4–Sept. 9, mimeo.
- Pasurka, Carl, 2003, “Changes in emissions from U.S. manufacturing: a joint production perspective,” Social Science Research Network, <http://papers.ssrn.com/abstract=418720>.
- Rose, Adam, 1999. Input–output structural analysis of energy and the environment. In: van den Bergh, Jeroen C.J.M. (Ed.), *Handbook of Environmental and Resource Economics*. Edward Elgar, Northampton, MA, pp. 1164–1179.
- Rose, Adam, Casler, Stephen, 1996. Input–output structural decomposition analysis: a critical appraisal. *Economic Systems Research* 8, 33–62.
- Selden, Thomas, Forrest, Anne, Lockhart, James, 1999. Analyzing the reductions in U.S. air pollution: 1970 to 1990. *Land Economics* 75, 1–21.
- Shestalova, Victoria, 2003. Sequential Malmquist indices of productivity growth: an application to OECD industrial activities. *Journal of Productivity Analysis* 19, 211–226.
- U.S. Department of Energy, Energy Information Administration, various years, FORM EIA-767, Steam–electric plant operation and design report.
- U.S. Federal Energy Regulatory Commission, various years, FERC form no. 1: Annual report of major electric utilities, licensees and others.
- Viguier, Laurent, 1999. Emissions of SO₂, NO_x, and CO₂ in transition economies: emission inventories and divisia index analysis. *The Energy Journal* 20, 59–87.
- Whitman, Requardt & Associates, LLP, 2002. The Handy–Whitman index of public utility construction costs: trends of construction costs, Bulletin No. 156 (1912 to July 1, 2002), Baltimore, MA.
- Wier, Mette, 1998. Sources of changes in emissions from energy: a structural decomposition analysis. *Economic Systems Research* 10, 99–112.
- Wier, Mette, Hasler, Berit, 1999. Accounting for nitrogen in Denmark—a structural decomposition analysis. *Ecological Economics* 30, 317–331.

- Yaisawarng, Suthathip, Klein, J. Douglass, 1994. The effects of sulfur dioxide controls on productivity change in the U.S. electric power industry. *Review of Economics and Statistics* 76, 447–460.
- Zaim, Osman, 2004. Measuring environmental performance of state manufacturing through changes in pollution intensities: a DEA framework. *Ecological Economics* 48, 37–47.