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Pollution Abatement and Employment

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Abstract

Morgenstern et al. (2002) is well-known for its investigation of the employment effects of environmental regulations. However, the cost function specified in that paper is handicapped by its reliance on survey data of the costs of inputs assigned to pollution abatement. In this paper, we specify an input distance function that models the joint production of good and bad outputs. This allows us to measure the relative importance of factors associated with changes in employment without pollution abatement cost data. We operationalize our model using a sample of 80 coal-fired electric power plants from 1995–2005.

Keywords

environmental technology; pollution abatement; employment; decomposition; L94; Q52

1. Introduction

Pollution abatement causes a reallocation of inputs from producing a marketed (good) output to pollution abatement whose output is reduced levels of the bad output (i.e., the undesirable by-product of producing the good output). For a given technology and quantity of inputs (e.g., labor and capital), the opportunity cost of reducing bad outputs (e.g., sulfur dioxide) is reduced production of good outputs (e.g., electricity generation). This led to ongoing interest in determining the extent of adverse effects on an economy's production of its good outputs when environmental regulations reduce bad outputs (see Pasurka 2008). Recently, concerns about the effects of pollution abatement have expanded to include their effect on employment. While in the long-run pollution abatement has no net effect on

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employment, it does reallocate inputs among firms within a sector and among sectors of the economy. These input reallocation consequences are frequently a source of concern to a society. This has led to efforts to understand the extent of the role played by pollution abatement to changes in employment.

Morgenstern et al. (2002) specified an econometric model that decomposed the change in employment due to environment regulation into two production effects - (1) a factor shift effect and (2) a cost effect. They examined how changes in regulatory intensity affected plant-level employment if the observed level of good output production was maintained. The factor shift component identifies the association between changes in labor cost shares due to changes in regulatory intensity, which reflect changes in the labor intensity of production, and changes in employment. The cost effect component reflected an increase in total production costs due to more stringent regulation. For example, if input cost shares are constant, increased production costs yield increased labor costs due to the cost effect.

Summing these plant-level employment changes, while holding good output production constant, allowed them to calculate changes in industry-level employment. Finally, they identified demand responses to industry-level price changes and estimated how that affected plant-level employment. In their model, lower employment due to the demand effect occurred when an increase in the stringency of environmental regulations – where the regulatory stringency is reflected by the cost of inputs assigned to pollution abatement - results in higher production costs, which results in higher prices for the good output and a corresponding decline in its quantity demanded.

Instead of survey estimates of the cost of inputs assigned to pollution abatement, Berman and Bui (2001) used three binary indicators that account for the year a regulation was adopted, the year a regulation became more stringent, and the year a plant complied with the regulation. They proposed a similar decomposition strategy for a cost function in which pollution abatement affects the demand for labor via two transmission mechanisms. First, an output effect, in which environmental regulations will likely reduce production of the good output. This is comparable to the scale effect in Morgenstern et al. (2002). Second, the marginal rate of technical substitution between pollution abatement (a quasi-fixed factor) and variable inputs (i.e., labor) not assigned to pollution abatement is comparable to the factor shift effect in Morgenstern et al. (2002). The effect of this mechanism on labor demand hinges on whether pollution abatement is a complement (end-of-pipe abatement) or substitute (change-in-process) for labor. They hypothesize that end-of-pipe technologies need workers for operation and maintenance, while change-in-process abatement techniques and labor are substitutes because change-in-process abatement technologies reduce the amount of pollution created. This results in fewer workers needed to dispose of the undesirable byproducts. Unlike Berman and Bui (2001) and Morgenstern et al. (2002), our use of a balanced panel dataset precludes an investigation of the role of regulatory induced exits of plants from the industry on changes in employment.

The cost function specified in Morgenstern et al. (2002) relies on survey data of the costs of inputs assigned to pollution abatement to identify the cost of regulations. The decline in efforts to collect data on the cost of inputs assigned to pollution abatement in the United

States, hampers future efforts to implement the decomposition strategies developed in those papers. In an attempt to maintain some of Morgenstern et al. (2002) framework, this paper adopts and extends the “production effects” of the model by specifying an alternate theoretical framework that obviates the need for data on the costs of inputs assigned to pollution abatement.

Färe et al. (2013) examined the extent of non-optimal employment levels among coal-fired electric power plants due to the lack of “mobility” of bad output production among the plants. While Masur and Pozner (2013) estimated adjustment costs associated with short-run unemployment due to changes in environmental regulations, Färe et al. (2013) focused on over-employment associated with inefficiencies due to bad outputs not being reduced in the most cost-effective manner. Others including Berman and Bui (2001), Gray and Shadbegian (2013), Gray et al. (2014), and Ferris et al. (2014) have examined the impact of environmental regulation on net employment in the regulated sector. In general, these studies find that environmental regulation has a negligible effect on employment.¹ Belova et al. (2015) reviews the extant literature on the link between environmental regulation and jobs.

Previous efforts that employed DEA models to assess the relative importance of factors associated with input changes have focused on labor or energy. Kumar and Russell (2002) used an output-oriented DEA model to decompose labor productivity growth into the effects of technological change (shifts in frontier), changes in technical efficiency (catching up or falling behind the frontier), and capital accumulation (movement along frontier). This framework was subsequently extended by papers such as Henderson and Russell (2005) and Los and Timmer (2005). In a separate branch of the literature, several papers have used DEA models to decompose changes in energy consumption. These papers include the output-oriented DEA models of Wang (2007) who decomposed energy productivity and Wang (2013) who decomposed changes in energy intensity – the reciprocal of energy productivity – into five components: (1) technological catch-up, (2) technological progress, (3) changes in the capital-energy ratio, (4) changes in the labor-energy ratio and (5) changes in the output structure. Finally, Wu et al (2012) used a sub-vector distance function that modeled the bad output using the traditional specification of weak disposability to decompose changes in energy efficiency into its technical change and change in technical efficiency components.

Previous DEA decomposition models of changes in bad outputs or changes in input use have specified either regulated or unregulated production technologies, where the regulated technology exhibits weak output disposability and null-jointness while the unregulated technology exhibits outputs that are strongly disposable. In this paper, we use a variation of the Färe et al. (2013) labor-oriented DEA framework that incorporates both regulated and unregulated production technologies. Unlike Färe et al. (2013), we use an input distance function to determine the relative importance of factors in explaining changes in employment among coal-fired electric power plants.

When considering the effect of pollution abatement on good output production, we specify the environmental technology to model the joint production of good and bad outputs when

¹Greenstone (2002), Walker (2011), and Walker (2013) examine the effect of environmental regulations on the gross employment.

production of the bad output is regulated.² An important feature of joint production models is that they do not require assigning input costs to good output production and pollution abatement.³

This paper investigates the association between pollution abatement and employment by combining the production effect components developed by Morgenstern et al. (2002) with the decomposition strategies proposed by Pasurka (2006) and Färe et al. (2016). We decompose changes in plant-level employment from a production perspective starting with the cost effect that compares employment when bad outputs are unregulated (i.e., the bad outputs are freely disposable) to when bad outputs are regulated (i.e., the bad outputs are not freely disposable). The cost effect, which measures the increased employment associated with the regulated technology, represents the opportunity cost of pollution abatement in terms of employment. Next, we identify several sources of changes in employment associated with the regulated technology: (1) changes in technical efficiency (i.e., catch-up), (2) technical change, (3) changes in the mix of labor and non-labor (i.e., capital and fuels) inputs, and (4) changes in good output and bad output production. Unlike Morgenstern et al. (2002) which used data on the cost of inputs assigned to pollution abatement to identify the cost of regulations, we address the issue by modeling the joint production of good and bad outputs as weakly disposable.

The remainder of this paper is organized in the following manner. In Section II, we discuss the input distance function framework used to measure the effect of factors on changes in the employment of coal-fired electric power plants, while in Section III we present the decomposition framework. In Section IV after discussing the data, we present the results of a decomposition of the sources of change in employment using a sample of coal-fired electric power plants from 1995 through 2005. Finally, Section V summarizes this paper.

2. The Model

In this paper, we construct isoquants when the plant is allowed to freely dispose the bad outputs it produces - henceforth referred to as “unregulated” isoquants, and isoquants when the plant is not allowed to freely dispose the bad outputs it produces – henceforth referred to as “regulated” isoquants. These isoquants calculate the minimum level of inputs necessary for each plant to produce its observed quantities of good and bad outputs under different assumptions about how a plant may treat the bad outputs it produces. Each isoquant, whether it reflects the unregulated or regulated technology, shows different combinations of labor and non-labor inputs that can produce a given level of good output production. In addition, each isoquant under regulation is constructed for a given level of bad output production. The ratio of employment with the regulated technology relative to employment with the unregulated technology is the increased employment associated with the observed level of pollution abatement.

²The undesirable byproducts of good output production are not eliminated by pollution abatement. Instead, abatement activities transform undesirable byproducts from - for example - one media (air) to another media (solid waste) where it constitutes a reduced threat to human health. Baumgärtner et al. (2001) and Førsund (2009) investigate the material balance perspective of production models.

³Färe et al. (2007) provide a formal discussion of the environmental technology in which the environmental technology is specified as a linear programming problem.

In these models, plants are allowed to find neither a more efficient allocation of bad output production than their observed level of bad output production (see Färe et al. 2013), nor are they allowed to reallocate inputs among themselves (see Färe et al. 1992).

Data Envelopment Analysis (DEA) Model

We implement our model by specifying the environmental technology, which assumes weak disposability and null-jointness of the outputs. The latter concept tells us that producing good outputs requires producing bad outputs. When modeling the environmental technology, we assume b is an output - *not an input*. We also assume there are $k=1, \dots, K$ observations (power plants) of inputs and outputs.

Inputs other than labor are denoted by $x \in \mathbb{R}_+^N$, and labor is $L \geq 0$. The good output is $y \geq 0$ and the bad output is $b \geq 0$. Hence, for each plant there is a vector (x_k, L_k, y_k, b_k) , $k=1, \dots, K$ of observations. The output set for our production model is

$$P(x, L) = \{(y, b) : (x, L) \text{ can produce } (y, b)\}$$

which can be expressed as an Activity Analysis or DEA (Data Envelopment Analysis) model:

$$P(x, L) = \left\{ (y, b) : \begin{aligned} &\sum_{k=1}^K z_k y_k \geq y \\ &\sum_{k=1}^K z_k b_k \leq b \\ &\sum_{k=1}^K z_k x_{kn} \leq x_n, \quad n = 1, \dots, N \\ &\sum_{k=1}^K z_k L_k \leq L \\ &z_k \geq 0, \quad k = 1, \dots, K \end{aligned} \right\}. \quad (1)$$

Each combination of non-labor and labor inputs (x, L) , produces combinations of good and bad outputs (y, b) represented by the output set $P(x, L)$.^{4,5} The intensity variables z_k are the weights assigned to each of the K observations used to construct the isoquant.⁶

The good output is strongly disposable and together the good and bad outputs (y, b) are jointly weakly disposable.⁷ This is formally stated as:

⁴Because the specified production technology assumes plants are restricted to their observed production of bad outputs, the model assumes bad output production is immobile among plants.

⁵Because labor mobility is not permitted.

⁶For either the traditional or modified specification of weak disposability, non-increasing returns to scale can be modeled by adding this constraint to the LP problem: $\sum_{k=1}^K z_k \leq 1$. If the traditional specification of weak disposability is specified, Färe et al. (1986) outline how variable returns to scale are modeled.

$$(y, b) \in P(x, L), y' \leq y \Rightarrow (y', b) \in P(x, L)$$

which models strong disposability on the good output, and

$$(y, b) \in P(x, L), 0 \leq \theta \leq 1 \Rightarrow (\theta y, \theta b) \in P(x, L)$$

which models weak disposability on the good and bad outputs. Imposing weak disposability on the good and bad outputs allows us to model the opportunity cost of reducing the bad outputs as the quantity of good output that must be foregone.⁸ Hence, weak disposability enables us to model the technology when bad outputs are not being treated as freely disposable. This can come about through either regulations or voluntary actions on the part of the producer. All inputs are strongly disposable (i.e., non-negative marginal products) and the model exhibits constant returns to scale, since the z_k are just nonnegative.

The specification of the bad output constraint, which Färe et al. (2013, 2014) introduced, yields a $P(x, L)$ that is not bounded. The model can be easily adjusted so $P(x, L)$ is bounded (i.e., just set $b \leq \bar{b} = \max_k b_k$). This specification of the bad output constraint avoids the

possibility of a portion of the production frontier sloping downward (i.e., it restricts the shadow price of the bad output to be non-positive).

The input-oriented DEA model identifies technical inefficiency of a plant by measuring its maximum potential contraction of all inputs while maintaining its observed production of good and bad outputs.⁹ Our regulated model identifies the maximum contraction of inputs for each plant relative to its observed level of labor when the bad output is regulated and each plant is restricted to its *observed* level of good output production and bad outputs produced. This regulated technology can be expressed as an input distance function for period t :

$$D_t(x, L, y, b) = \left[\sup \lambda : \left(\frac{x}{\lambda}, \frac{L}{\lambda}, y, b \right) \in T \right] \quad (2)$$

⁷ $(y, b) \in P(x, L), (x', L') \in P(x, L) \Rightarrow (y, b) \in P(x', L')$ defines strong disposability of the inputs; while $P(\lambda x, \lambda L) \Rightarrow \lambda P(x, L), \lambda \geq 0$, defines constant returns to scale.

⁸Weak disposability, which was introduced by Shephard (1970), is the proportional reduction in all good and bad outputs. Here we apply the concept to inputs.

⁹A sub-vector labor input distance function identifies technical inefficiency by calculating the maximum contraction of labor that combined with the observed levels of non-labor inputs (capital and fuels) allows a plant to maintain its observed production of good and bad outputs. Like the input distance function, specifying a sub-vector labor input distance function imposing weak disposability on bad outputs results in the possibility of infeasible mixed-period LP problems. For example, when the technology of period t is used to evaluate the performance of an observation from period $t+1$, the calculations can determine that the observed data in period $t+1$ is not feasible in period t . This occurs when the observation $(y^{t+1, k}, b^{t+1, k})$ does not belong to the output set $P^t(x^{t+1})$. We employed two strategies in an attempt to eliminate the occurrence of infeasible LP problems. First, only period $t+1$ was used as the reference technology for mixed-period LP problems. Second, 2-year windows were employed for the reference technology. In other words, the isoquant for period $t+1$ is constructed with observations from period t and period $t+1$. Hence, all observations $(y^{t, k}, b^{t, k})$ being evaluated (i.e., right-hand side observations) are included in the reference technology. However, these strategies did not eliminate the occurrence of infeasible mixed-period LP problems. As a result, we specify an input distance function in this paper that scales on all inputs.

where $T = \{x, L, y, b\} : (y, b) \in P(x, L)\}$ and λ represents the maximum feasible contraction of all inputs at a plant. Hence, $D_i(x, L, y, b)$ - the reciprocal of the Farrell efficiency measure - allows us to solve for the ratio of a plant's observed level of labor relative to its efficient level of labor. It follows that $D_i(x, L, y, b) = 1$ where a value of unity indicates an observation is efficient and a value exceeding unity indicates inefficiency. As a result, L/λ is the amount of labor the plant would employ if it were efficient given its observed good output production and bad output production.

The regulated model calculates the maximum contraction of all inputs required by each plant that allows it to produce at least its observed level of good and no more than its observed level of bad outputs. Hence, the linear programming (LP) problem for the regulated input distance function is:

$$D_i(X_{k'}, L_{k'}, y_{k'}, b_{k'})^{-1} = \min \quad \lambda \quad (3)$$

$$s.t. \quad \sum_{k=1}^K z_k x_k \leq \lambda x_{k'}$$

$$\sum_{k=1}^K z_k L_k \leq \lambda L_{k'}$$

$$\sum_{k=1}^K z_k y_k \geq y_{k'}$$

$$\sum_{k=1}^K z_k b_k \leq b_{k'}$$

$$z_k \geq 0, k = 1, \dots, K$$

The unregulated production technology modifies the regulated technology by not including bad output production. Since all observations reflect a certain level of pollution abatement, the unregulated technology might be more accurately thought of as the least-regulated observed technology. This technology is represented by the following input distance function

$$D_i(x, L, y) = \left[\sup \lambda : \left(\frac{x}{\lambda}, \frac{L}{\lambda}, y \right) \in T \right] \quad (4)$$

which calculates a plant's maximum contraction of all inputs that allows it to produce at least its observed quantity of good output. Hence, $L/D_i(x, L, y)$ is the minimum (i.e., technically efficient) level of labor required by a plant to operate on its unregulated isoquant.

From the input distance functions, non-labor inputs, good and bad output production, and the regulated technology determine employment for the regulated technology, while non-labor inputs, good output production, and the unregulated technology determine employment for the unregulated technology. Hence, the LP problem for the unregulated technology starts

with the LP problem for the regulated technology (equation 3) and removes the constraint on bad output production.

3. Sources of Employment Changes

Formally defining the employment effects of pollution abatement in the previous section required specifying technologies describing the production of *one* good output when the bad output is freely disposable - the unregulated technology, and another technology for when the bad output is not freely disposable - the regulated technology. Hence, the distance function for the regulated technology includes bad outputs (b), while bad outputs are not included in the distance function for the unregulated technology. Having identified the efficient level of labor for the regulated technology (2) and unregulated technology (4), we specify the Cost Effect (CE) for period t as

$$CE^t = \left[\frac{L^t/D_i^t(x^t, L^t, y^t, b^t)}{L^t/D_i^t(x^t, L^t, y^t)} \right] = [D_i^t(x^t, L^t, y^t)/D_i^t(x^t, L^t, y^t, b^t)] \quad (5)$$

while for period $t+1$ it is

$$\begin{aligned} CE^{t+1} &= \left[\frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1})} \right] \\ &= [D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1})/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})] \end{aligned} \quad (6)$$

It follows from (2) and (4) that CE^t and CE^{t+1} are ratios of the efficient level of labor when the bad output is regulated relative to the efficient level of labor when the bad output is unregulated (i.e., least regulated). It follows that CE, which measures the increased employment associated with the regulated technology, is the opportunity cost of pollution abatement in terms of employment. Because the value of the unregulated input distance function is greater than or equal to the value of the regulated input distance function, CE^t and CE^{t+1} are greater than or equal to unity.¹⁰ Therefore, the efficient level of labor for the unregulated technology is less than or equal to the efficient level of labor for the regulated technology. It follows – *ceteris paribus* - that an increase in regulatory stringency in period $t+1$ relative to period t increases the level of labor required by the regulated technology relative to labor requirements of the unregulated technology, which results in $CE^{t+1} > CE^t$.

Summing the efficient level of labor for each plant yields the efficient level of employment within the industry when the bad output is regulated. The ratio in the efficient level of employment between the regulated and unregulated isoquants represents the increased

¹⁰Because the bad output constraint is excluded from the specification of the unregulated input distance function, it follows that the value of the unregulated input distance function is greater than or equal to the value of the regulated input distance function. In other words, the unregulated technology can produce the same level of the good output as the regulated technology with no more (and maybe fewer) inputs.

quantity of labor associated with the existing level of pollution abatement. Hence, the increased labor needed to reduce bad output production, while maintaining the observed good output production, represents the *cost effect* in our model.

By combining equations (5) and (6), the change in employment due to the change in CE can be written as:

$$\Delta CE_t^{t+1} = \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}) / D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{\frac{D_i^t(x^t, L^t, y^t) / D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}) / D_i^t(x^t, L^t, y^t)}} \right] \quad (7)$$

$$= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}) / D_i^t(x^t, L^t, y^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1}) / D_i^t(x^t, L^t, y^t, b^t)} \right]$$

where ΔCE_t^{t+1} is an index of the ratio of the efficient level of labor for the regulated and unregulated (i.e., least regulated) isoquants in period t+1 and period t. The change in employment due to ΔCE_t^{t+1} is calculated by taking the ratio of the input distance functions for the unregulated technology of period t+1 and period t relative to the ratio of the input distance functions for the regulated technology of period t+1 and period t. Hence, ΔCE_t^{t+1} is the ratio of the ratio of the efficient level of labor when the bad output is regulated – in period t+1 and period t – relative to the ratio of the efficient level of labor when the bad output is unregulated – in period t+1 and period t.

ΔCE_t^{t+1} shows whether the ratio of regulated to unregulated labor increases, decreases, or is constant between period t and period t+1. Thus, it calculates the change between period t and period t+1 in the higher level of employment due to regulation of the bad output. If the value of ΔCE_t^{t+1} exceeds unity, the cost effect increases (i.e., there is an increase in the gap between the regulated and unregulated isoquants) between period t and period t+1. In other words, the higher level of employment due to pollution abatement increases. A ΔCE_t^{t+1} value of less than unity signifies a decrease in the cost effect (i.e., there is a decrease in the labor gap between the regulated and unregulated isoquants), while a value of unity indicates the cost effect is unchanged between period t and period t+1.

Li and Chan (1999), which is discussed in Grosskopf (2003), extended the Färe et al. (1994) output-oriented decomposition framework by decomposing changes in good output production into changes in technical efficiency, technical change, and changes in inputs. In this paper, we extend the Li and Chan model by specifying an input-oriented model (see Färe et al. 1992) that includes bad outputs in the specification of the production technology.

Building upon the labor oriented model specified in Färe, et al. (2013), the decomposition model specified in this paper combines features of the models specified in Pasurka (2006) and Färe et al. (2016).¹¹ Pasurka (2006) investigated sources of changes in bad output production using only the regulated technology, while Färe et al. (2016) investigated sources

of changes in the ratio in the maximum good output that can be produced by the unregulated and regulated technologies.

Using period $t+1$ as the reference period for mixed-period LP problems, we decompose the change in the technically efficient level of employment between period t and period $t+1$ for the regulated technology (i.e., the value on the left-hand side of the expression is the ratio of the denominators in equations 6 and 5) into three components:

$$\begin{aligned} \frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^t/D_i^t(x^t, L^t, y^t, b^t)} &= \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \\ &\times \left[\frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^t, b^t)}{L^t/D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \\ &= (TC_r) \times (IC_r) \times (OC_r) \end{aligned} \quad (8)$$

where TC_r is the change in employment due to technical change, IC_r is the change due to changes in the mix of labor and non-labor inputs, and OC_r is the change associated with changes in the mix of good and bad outputs (i.e., the emission intensity).¹²

The TC component reflects shifts in the regulated isoquants between period t and period $t+1$, while the IC_r component reflects movements along the regulated isoquants of period t and period $t+1$. Hence, IC_r captures the *factor-shift effect* of Morgenstern et al. (2002), which identifies changes in employment resulting from changes in non-labor factors of production. Finally, OC_r captures the change in output mix effect on employment between period t and period $t+1$.

If the plant is efficient in period t (i.e., $D_i^t(x^t, L^t, y^t, b^t) = 1$) and period $t+1$ (i.e., $D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1}) = 1$), then equation (8) is adequate for decomposing sources of change in labor. However, if the plant is inefficient in period t and/or period $t+1$, i.e., $D(\bullet) > 1$ then it is necessary to decompose the change in the observed level of labor in periods $t+1$ and t (i.e., L^{t+1}/L^t). This requires introducing a new factor – the change in technical efficiency – into the decomposition analysis. This is accomplished by multiplying both sides of equation (9) by $\left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right]$. Using period $t+1$ as the reference technology, the change in the observed level of labor between period t and period $t+1$ is

¹¹Appendix A provides a detailed derivation of the association between the decomposition proposed in this paper and decomposition strategies proposed by Wang (2007, 2013) and Li (2010).

¹²The product of IC_r and OC_r is $\left[\frac{L^{t+1}}{L^t} \right] \times \left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right]$ where $\left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right]$ is the reciprocal of the Malmquist productivity index when period $t+1$ is the reference technology (see Färe et. al., 1992).

decomposed into four components, the three components found in (8) plus the change in technical efficiency:

$$\begin{aligned}
 \Delta L_i^{t+1} &= \left[\frac{L^{t+1}}{L^t} \right] \\
 &= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \\
 &\quad \times \left[\frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^t, b^t)}{L^t/D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \\
 &= (TE_r) \times (TC_r) \times (IC_r) \times (OC_r)
 \end{aligned} \tag{9}$$

where TE_r , is the change in employment due to changes in technical efficiency, which reflects whether between period t and $t+1$ an observation moved closer to or further from the best-practice regulated isoquant.¹³

Changes in technical efficiency measure whether an observation is “catching up” (increased technical efficiency) or “falling behind” (decreased technical efficiency) the regulated isoquant (i.e., when the producer cannot freely dispose its bad output production). Improved technical efficiency ($TE_r < 1$) decreases employment, while decreased technical efficiency ($TE_r > 1$) increases employment. The technical change effect captures changes in employment due to shifts in the regulated isoquant. Technical progress ($TC_r < 1$) decreases employment while technical regress ($TC_r > 1$) increases employment. Likewise, for IC_r and OC_r a value exceeding unity indicates the component is associated with increasing L between period t and period $t+1$, while a value less than unity signifies the component is associated with declining L . Finally, a value of unity indicates the component is associated with no change in L .¹⁴ The direction of the effect of the input mix change (IC_r) and output mix change (OC_r) components on employment is an empirical issue. Changes in inputs may either increase or decrease employment depending upon whether the non-labor inputs are substitutes for labor or complements with labor. Finally, changes in the mix of good output and bad output mix may either increase or decrease employment.

For the TC_r , IC_r , and OC_r components, we prefer using geometric means of the results with period t and period $t+1$ as reference technologies because this allows us to avoid selecting an arbitrary reference technology. Unfortunately, infeasible LP problems occur for mixed-period problems when using contemporaneous frontiers and when the mixed-period problem uses the technology from period t to evaluate an observation from period $t+1$.¹⁵ We avoid infeasible LP problems by employing two strategies. First, we use only period $t+1$ as the

¹³If there is no pollution abatement, only the unregulated technology is relevant and all observations above the isoquant are technically inefficient.

¹⁴If the goal is to decompose either labor intensity (L/Y) or labor productivity (Y/L) the model introduced by Wang (2007, 2013) to decompose energy intensity and energy productivity can be modified to decompose either L/Y or Y/L .

¹⁵A mixed-period LP starts with the LP problem in (3) and has time superscripts on the right-hand side of the constraints differing from the time superscripts on the left-hand side of the constraints. For example, the observation whose efficiency is being calculated -

reference technology for mixed-period LP problems. This avoids infeasible LP problems that occur when the technology of period t is used to evaluate observation from period $t+1$. Second, we use 2-year windows when constructing the reference technology. In other words, the technology for period $t+1$ (e.g., 2002) is constructed from observations from period t and period $t+1$ (e.g., 2001 and 2002). This ensures that all observation being evaluated are in the reference technology.¹⁶

4. Empirical Example: Background, Data and Results

The LP problems are operationalized using a balanced panel dataset of 80 coal-fired power plants from 1995–2005. Table 1 presents summary statistics of the data for 1995 and 2005.¹⁷ The sample size is dictated by the data available to produce a balanced panel for 1995–2005. The technology modeled in this study consists of one good output - “net electrical generation” (KWH), and bad output - SO_2 . The inputs are the capital stock (in constant dollars), 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). The power plants may consume coal, oil, or natural gas; however, in order to model a homogeneous production technology coal must provide at least 95 % of the Btu of fuels consumed by each plant in each year.

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) is the source of labor and capital data for public power plants.^{18, 19} The U.S. Department of Energy (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. The EIA-767 survey (U.S. Department of Energy various years) is the source of information about fuel consumption, and net generation of electricity. The SO_2

the producer denoted k' - is from period $t+1$ and appears on the right-hand side of the constraints in the LP problem. The technology that is used to evaluate the observation consists of observations denoted k from period t and appears on the left-hand side of the constraints.

¹⁶Appendix B contains the specification of the decomposition for both the case with period t as the reference technology for the mixed-period LP problems and the case when geometric means of the results when period t and period $t+1$ are the reference technology. In addition, a diagrammatic example is provided for the three cases (1) period $t+1$ is the reference technology, (2) period t is the reference technology, and (3) the geometric mean of the results when period t and period $t+1$ as the reference technologies.

¹⁷The LP problems are solved using GAMS/MINOS. The GAMS programs and appendices are available from the corresponding author upon request.

¹⁸Data on the cost of plant and equipment for years prior to 1981 were published in annual reports from the Federal Power Commission and the Energy Information Administration. The Utility Data Institute (1999) provides 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.

¹⁹While 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 & Klein (1994, p. 453, footnote 30) and Carlson et. al. (2000, p. 1322). We then convert the historical cost of plant data to constant dollar values using the Handy-Whitman Index (HWI) (see Whitman, Requardt & Associates, LLP 2012). 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.

emission data are collected by the U.S. EPA Continuous Emissions Monitoring System (CEMS).

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

The LP programs generate the technically efficient level of labor for the unregulated and regulated technologies of each power plant for each year in our sample. This allows us to calculate the CE for each plant in 1996 through 2005. In 1996, the geometric mean of CE for the 80 plants is 1.0153. Of the 80 plants, 45 had CE values of unity (no increased employment due to pollution abatement) in 1996, and Carbon (3644) had the maximum CE of 1.1938. In 2005 the geometric mean of the CE for the 80 plants is 1.0220. In 2005, 46 plants had CE values of unity, and Dave Johnston (4158) had the maximum CE of 1.1873.

We also calculate CE, L and its components for each two-year pair from 1996 through 2005 for each of the 80 plants in our sample. In Table 2, we present results for the average plant for each two-year period. It can be seen that during 1996–2005 CE is associated with an average annual increase in employment of 0.07 percent. The increased employment associated with CE reflects differences in shifts of the unregulated and regulated isoquants. As a result, the average value of CE is greater than unity due to its value equaling or exceeding unity for each 2-year pair from 2001–2005.

During 1996–2005, the level of employment (L) declined by 1.26 percent annually. Due to a decrease in technical efficiency, TE_t is associated with an average annual increase in employment of 0.14 percent, while TC_t is associated with an average annual decrease in employment of 0.31 percent. Given that technical progress reduces employment required to produce a given level of output, it is not surprising that TC_t is associated with decreased employment. In addition, IC_t is associated with an average annual decrease in employment of 1.94 percent and OC_t is associated with an average annual increase in employment of 0.86 percent. The decrease associated with IC_t is due to its value being less than unity for each 2-year pair during 1996–2000, while the increase associated with OC_t is due its value exceeding unity for each 2-year pair during 1996–2000. Comparing the mean values of the outputs in Table 1 reveals that during 1995–2005 the reduced employment associated with IC_t occurred during a time of declining employment at the average plant. For the non-labor inputs, between 1995 and 2005 the capital stock and coal consumption increased, while oil and natural gas consumption decreased. Hence, the results for IC_t suggest a higher capital-labor ratio and a higher coal-labor ratio are associated with lower employment. Comparing the mean values of the outputs in Table 1 reveals that during 1995–2005 the increased employment associated with OC_t occurred during a reduction in the emission-intensity of production (i.e., a decline in the ratio of the bad output to the good output) at the average plant. Hence, the results for OC_t reveal that declining emission-intensity is associated with increased employment. While the decline in employment associated with TC_t for the typical

plant suggests that technical change is biased toward labor-saving technology, the reduced employment due to the IC_r effect is even more pronounced. The OC_r results hint that pollution abatement is labor-intensive for electricity production for the average plant in the sample.

Table 3 presents the average two-year pair results for CE , L and its components for each power plant. The mean values for the CE index of plants range from 1.0169 for Dave Johnston (4158) to 0.9879 for Carbon (3644). Of the 80 plants, 25 report an average CE that is greater than unity, 37 report a value of unity, and 18 report values less than unity. The mean values for the L index of plants range from 1.0466 for Mill Creek (1364) to 0.9076 for Rivesville (3945). Of the 80 plants, 17 report an average L that is greater than unity (i.e., an increase in the number of employees), 2 report a value of unity, while 61 report values less than unity (i.e., a decrease in the number of employees). Mean values of TE_r for individual plants range from 1.0181 for Carbon (3644) to 0.9821 for Dave Johnston (4158). Of the 80 plants, 48 report an average TE_r that is greater than unity, 6 report a value of unity, and 26 report values less than unity. Mean values of TC_r for individual plants range from 1.0112 for Dave Johnston (4158) to 0.9828 for St. Clair (1743). Of the 80 plants, 13 report an average TC_r that is greater than unity, 1 reports a value of unity, while 66 report values less than unity. The range of mean values of IC_r extend from 1.0686 for Bailly (995) to 0.8683 for Rivesville (3945). Of the 80 plants, 15 report an average IC_r that is greater than unity, while 65 report values less than unity. Finally, mean values of OC_r , ranged from 1.0611 for Hammond (708) to 0.9185 for Bailly (995). Of the 80 plants, 55 report an average OC_r that is greater than unity, while 25 report values less than unity.

In summation, from 1995–2005, the average level of employment at a plant in our sample declines by almost 20 percent. During 1996–2005, the cumulative geometric mean level of employment (L) declines by 10.78 percent. This decline is driven by the TC_r component, which is associated with a cumulative 2.76 percent decline in employment, and the IC_r component, which is associated with a cumulative 16.16 percent decline in employment. Some of the downward trend in employment is offset by the cumulative 8.01 percent increase in employment associated with the OC_r component. It is interesting to note that all of these are substantially larger – in absolute terms – than the cumulative 0.63 percent increase in employment associated with the CE component.

5. Conclusions

For several decades, there have been concerns about the potential adverse consequences for the economy of efforts to reduce releases of bad outputs into the environment. While the prime focus has been on reduced good output production associated with pollution abatement, concerns have also been expressed about how pollution abatement may negatively affect employment.

The model proposed in this paper reimagines the decomposition specified in Morgenstern et al. (2002) without data on the cost of inputs assigned to pollution abatement. Instead of the cost function approach employed by Morgenstern et al., we combined input distance functions with different assumptions about output disposability to demonstrate that it is

feasible to undertake the type of decomposition found in Morgenstern et al. without information on the cost of inputs assigned to pollution abatement. With the cessation of efforts to collect data on the cost of inputs assigned to pollution abatement by industries in the United States, the model proposed in this paper emerges as the best available structural model for determining the employment effects of pollution abatement.

In addition to modeling the relative importance of factors associated with changes in employment, the labor constraint in the model can be modified to allow labor mobility among plants, which would reveal the effect of short-run rigidities that limit mobility in the labor market on employment (see Masur and Pozner 2013). By comparing the short-run and long-run results, it is possible to calculate the employment effects associated with short-run rigidities that limit labor mobility among plants within an industry or among industries in the economy. Extending our model to incorporate input mobility that respond to changes in demand for the output of the electric power industry would allow it to measure a variation of the *demand effect* of regulations on employment (see Morgenstern et al. 2002 and Morgenstern 2013).

The primary purpose of the empirical portion of this paper was to demonstrate that it is practical to operationalize the theoretical model proposed in the paper. With the necessary data, the model can be expanded to include changes in employment among different industries in an economy. Comparing employment changes across industries with differing levels of abatement intensity would allow the model to more closely resemble Morgenstern et al. (2002).

Finally, if data are available, a nonparametric cost function with good and bad outputs (see Ball et al. 2005) that allows for weak disposability provides an alternative option for assessing the association between pollution abatement and employment. Using a cost function would allow the model to more closely mirror the model employed by Morgenstern et al. (2002). Additionally, it might permit a more precise investigation of the backward incidence of pollution control (see Fullerton and Heutel 2010).

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Appendix A: (Not intended for publication)

An alternate strategy for decomposing changes in labor is found in the output-oriented distance function decomposition proposed by Wang (2007), which decomposed changes in energy productivity, which is the change between period t and period $t+1$ in the good output (Y) produced per unit of energy input (E) (i.e., $\left[\frac{Y^{t+1}/E^{t+1}}{Y^t/E^t} \right]$). In addition, Wang (2013) proposed decomposing changes in energy intensity, which is the change between period t

and period $t+1$ in the energy consumed per unit of good output produced $\left[\frac{E^{t+1}/Y^{t+1}}{E^t/Y^t} \right]$. Li (2010) modeled the bad output as weakly disposable and decompose changes in bad output production (i.e., carbon emissions) (C^{t+1}/C^t) .¹ By substituting labor (L) for energy (E) in Wang (2007, 2013), we can demonstrate the association between the decompositions employed by Wang (2007, 2013), Li (2010), and our paper.

Following Wang (2007, p. 1328, equation 4), which decomposed $\left[\frac{Y^{t+1}/E^{t+1}}{Y^t/E^t} \right]$, we can write $\left[\frac{(Y/L)^{t+1}}{(Y/L)^t} \right]$ as:

$$\begin{aligned} \Delta(Y/L)_t^{t+1} &= \left[\frac{(Y/L)^{t+1}}{(Y/L)^t} \right] = \left[\frac{(Y^{t+1}/L^{t+1})}{(Y^t/L^t)} \right] & (9') \\ &= \left[\frac{(Y^{t+1}/L^{t+1})/D_i^{t+1}(x^t, L^t, y^t, b^t)}{(Y^t/L^t)/D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \\ &\times \left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^t(x^t, L^t, y^t, b^t)} \right] \\ &= \left[\frac{(Y^{t+1}/L^{t+1})}{(Y^t/L^t)} \right] \times (M_r) \times (TE_r) \times (TC_r) \\ &= (PLPCH_r) \times (TE_r) \times (TC_r) \end{aligned}$$

where M_r is the input-oriented Malmquist productivity measure from Färe et al. (1992), while TE_r and TC_r are reciprocals of the input-oriented technical efficiency (TE) and technical change (TC) measures derived in Färe et al. (1992). $PLPCH_r$, which is $\left[\frac{(Y^{t+1}/L^{t+1})}{(Y^t/L^t)} \right] \times (M_r)$, maximum potential labor productivity change, which was introduced by Wang (2007) as the maximum potential energy productivity change (PEPCH).

Wang (2013) decomposed $\left[\frac{E^{t+1}/Y^{t+1}}{E^t/Y^t} \right]$, which is the reciprocal of the ratio decomposed by

Wang (2007). Following Wang (2013), we can write $\left[\frac{(L/Y)^{t+1}}{(L/Y)^t} \right]$ as:

¹While the technical change and change in technical efficiency expressions in Wang (2007) mirror Färe et al. (1994), the expressions for technical change and change in technical efficiency in Li (2010) and Wang (2013) are reciprocals of those in Färe et al. (1994).

$$\begin{aligned}
\Delta(Y/L)_t^{t+1} &= \left[\frac{(L/Y)^{t+1}}{(L/Y)^t} \right] = \left[\frac{(L^{t+1}/Y^{t+1})}{(L^t/Y^t)} \right] \quad (9'') \\
&= \left[\frac{(L^{t+1}/Y^{t+1})/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{(L^t/Y^t)/D_i^t(x^t, L^t, y^t, b^t)} \right] \\
&\times \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \\
&= \left[\frac{(L^{t+1}/Y^{t+1})}{(L^t/Y^t)} \right] \times (M_r) \times (TE_r) \times (TC_r) \\
&= (1/PLPCH_r) \times (TE_r) \times (TC_r)
\end{aligned}$$

where M_r is the reciprocal of the input-oriented Malmquist productivity measure from Färe et al. (1992), while TE_r and TC_r are the input-oriented technical efficiency (TE) and technical change (TC) measures derived in Färe et al. (1992). $(1/PLPCH_r)$, which is $\left[\frac{(L^{t+1}/Y^{t+1})}{(L^t/Y^t)} \right] \times (M_r)$, is the reciprocal of PLPCH. Since $PLPCH_r$ is the maximum potential labor productivity change, $(1/PLPCH_r)$ represents the maximum potential energy intensity change (see Zhou and Ang 2008, p. 1057).

Multiplying both sides of (9'') by $[Y^{t+1} / Y^t]$ yields the following (see Li 2010, p. 78, equation 3):

$$\begin{aligned}
\left[\frac{L^{t+1}}{L^t} \right] &= \left[\frac{Y^{t+1}}{Y^t} \right] \times \left[\frac{(L^{t+1}/Y^{t+1}) \times D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{(L^t/Y^t) \times D_i^t(x^t, L^t, y^t, b^t)} \right] \quad (9''') \\
&\times \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \\
&= (SC_r) \times \left[\frac{L^{t+1}/Y^{t+1}}{L^t/Y^t} \right] \times (M_r) \times (TE_r) \times (TC_r) \\
&= (SC_r) \times (1/PLPCH_r) \times (TE_r) \times (TC_r)
\end{aligned}$$

This transformation allows Li (2010) to introduce a scale effect (SC) component (Y^{t+1} / Y^t) that is absent from Wang (2007, 2013). As was the case for (9''), M_r is the reciprocal of the input-oriented Malmquist productivity measure from Färe et al. (1992), while TE_r and TC_r are the input-oriented technical efficiency (TE) and technical change (TC) measures derived in Färe et al. (1992).²

If we start with (9) in our paper and take the product of (IC_r) and (OC_r) , this yields:

$$\begin{aligned}
\Delta L_t^{t+1} &= \left[\frac{L^{t+1}}{L^t} \right] & (9''') \\
&= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{L^{t+1}}{L^t} \right] \\
&\times \left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \\
&= (TE_r) \times (TC_r) \times \left[\frac{L^{t+1}}{L^t} \right] \times (M_r)
\end{aligned}$$

where (M_r) is the reciprocal of the input-oriented Malmquist productivity measure (see Färe et al., 1992).³ TC_r and TE_r mirror the Färe et al. (1992) input-oriented distance function expressions for technical change (TC) and technical efficiency (TE). It can be seen that the Y^t and Y^{t+1} on the right-hand side of $(9''')$ cancel out each other which reveals that $(9''')$ and $(9''')$ are identical.

The final step taken by Wang (2007 and 2013) is decomposing the PEPCH (the energy counterpart of PLPCH) component into its sub-components. Using an output-oriented distance function, Wang (2007) decomposed energy productivity, $\left[\frac{Y^{t+1}/E^{t+1}}{Y^t/E^t} \right]$, into its TC and TE components and then decomposed the residual (PEPCH) into the following four sub-components: (1) changes in the capital-energy ratio, (2) changes in the labor-energy ratio, (3) changes in energy supply composition, and (4) changes in the output structure of the economy. Using an output-oriented distance function, Wang (2013) decomposed energy-intensity, $\left[\frac{E^{t+1}/Y^{t+1}}{E^t/Y^t} \right]$, into its TC and TE components and then decomposed the residual into the following three sub-components: (1) changes in the capital-energy ratio, (2) changes in the labor-energy ratio, and (3) changes in the output structure of the economy.

There are several differences between our decomposition model and those proposed by Wang (2007, 2012) and Li (2010). First, Li (2010) and Wang (2007 and 2013) use output-oriented distance functions. We use an input-oriented distance function in our paper. Second, Li (2010) and Wang (2013) uses both t and $t+1$ as reference periods for mixed-period LP problems, while Wang (2007) uses only period t for the reference technology for mixed-period LP problems. In order to avoid infeasible LP problems, we use only period $t+1$ as the reference technology for our mixed-period LP problems. Third, unlike Wang (2007, 2013)

²Zhou and Ang (2008) proposed an alternative decomposition that combined input-oriented distance functions and output-oriented distance functions to decompose changes in CO_2 . Among the seven factors included in their decomposition of changes in CO_2 emissions were (1) a scale effect, (2) technical change, and changes in technical efficiency.

³The product of IC_r and OC_r is $\left[\frac{L^{t+1}}{L^t} \right] \times \left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right]$ where $\left[\frac{D_i^{t+1}(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right]$ is the reciprocal of the Malmquist productivity index when period $t+1$ is the reference technology (see Färe et al., 1992).

and Li (2010), we do not model multiple good outputs. Hence, there is no composition effect in our paper. Finally, Wang (2007, 2013) focused on changes in energy-productivity and changes in energy-intensity, while we investigate factors associated with changes in labor and labor intensity.

Appendix B: (Not intended for publication)

Cost Effect

The isoquants in Figure 1, which depict the unregulated and regulated technologies for period t and period $t+1$, provide a visual representation of the input distance functions (i.e., isoquants) used to define ΔCE_t^{t+1} . The regulated isoquant $(y_{Reg}^t, b_{Reg}^t, t)$ represents the combinations of labor and non-labor inputs that combined with regulated technology of period t allows the plant to produce the observed level of good output, while the unregulated isoquant (y_{Unreg}^t, t) represents the combinations of labor and non-labor inputs that combined with unregulated technology of period t allows the plant to produce the observed level of the good output. Point a , which lies above the regulated isoquant $(y_{Reg}^t, b_{Reg}^t, t)$, represents an inefficient plant in period t . The LP problems calculate the ratio between an observed level of labor and the efficient level of labor. Thus, for the regulated technology in period t (equation 3) the LP problem calculates OB/Oa , which is the reciprocal of the input distance function (Oa/OB) . While for the unregulated technology in period t , the LP problem calculates OC/Oa , which is the reciprocal of the input distance function (Oa/OC) . Hence, the ratio OB/OC shows CE_t .

For period $t+1$, the unregulated isoquant is $(y_{Unreg}^{t+1}, t+1)$, while the regulated isoquant is $(y_{Reg}^{t+1}, b_{Reg}^{t+1}, t+1)$. The observed use of labor and non-labor inputs in period $t+1$ is point e . Hence, the production process in period $t+1$ is labor-intensive relative to the period t process. The regulated technology in period $t+1$ (equation 3) the LP problem calculates OF/Oe , which is the reciprocal of the input distance function (Oe/OF) . While for the unregulated technology in period $t+1$, the LP problem calculates OG/Oe , which is the reciprocal of the input distance function (Oe/OG) . Hence, OF/OG shows CE^{t+1} . In terms of Figure 1, the change in employment due to the change in the cost effect, which is specified in equation (7), is:

$$\begin{aligned}\Delta CE_t^{t+1} &= \left[\frac{(Oe/OG)/(Oe/OF)}{(Oa/OC)/(Oa/OB)} \right] = \left[\frac{(OG/Oe)/(OF/Oe)}{(OC/Oa)/(OB/Oa)} \right] \quad (7') \\ &= \left[\frac{(OF/OG)}{(OB/OC)} \right] = \left[\frac{(OF/OB)}{(OG/OC)} \right]\end{aligned}$$

ΔCE_t^{t+1} changes as a result of changes in the unregulated and regulated isoquants. The unregulated isoquant shifts in response to technical change, input changes, or changes in good output production, while a regulated isoquant shifts in response to technical change, input changes, changes in good output production, or changes in bad output production. Because ΔCE_t^{t+1} measures changes in the ratio of labor employed by the regulated and

unregulated isoquants and not the sources of the change, we do not decompose the relative importance of factors associated with changes in the ratio of employment by the regulated and unregulated technologies. However, we are interested in decomposing changes in the observed level of labor relative to the efficient level of labor for the regulated technology. In terms of Figure 1, that involves identifying the factors associated with the change in employment in period t+1 (0e) relative to period t (0a).

Decomposition of Change in Employment – TC_r , IC_r , OC_r (Using period t and period t+1 as reference technologies)

In terms of Figure 2, equation (8) - the decomposition of the change in employment using period t+1 as the reference technology - can be written as:

$$\begin{aligned} \frac{0e/(0e/0F)}{(0a/(0a/0B))} &= \frac{0F}{0B} = \left[\frac{0a/0B}{0a/0J} \right] \times \left[\frac{0e/(0e/0K)}{0a/(0a/0J)} \right] \times \left[\frac{0e/0K}{0e/0F} \right] \quad (8') \\ &= (0J/0B) \times (0K/0J) \times (0F/0K) \\ &= (TC_r) \times (IC_r) \times (OC_r) \end{aligned}$$

The TC component reflects shifts in the regulated isoquants between period t and period t+1 (i.e., movement from point B to point J), while the IC_r component reflects movements along the regulated isoquants of period t and period t+1 (i.e., the movement from point J to point K). Hence, IC_r captures the *factor-shift effect* of Morgenstern et al. (2002), which identifies changes in employment resulting from changes in non-labor factors of production. Finally, movement from point K to point F captures the change in output mix effect on employment between period t and period t+1.

Alternately, the change in employment can be decomposed using period t as the reference period for mixed-period LP problems:

$$\begin{aligned} \frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, a^{t+1})}{L^t/D_i^t(x^t, L^t, y^t, a^t)} &= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \quad (8^*) \\ \times \left[\frac{L^{t+1}/D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^t/D_i^t(x^t, L^t, y^t, b^{t+1})} \right] &\times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^t(x^t, L^t, y^{t+1}, b^{t+1})} \right] \\ &= (TC_r) \times (IC_r) \times (OC_r) \end{aligned}$$

which in terms of Figure 2 can be written as:

$$\begin{aligned}
\frac{0e/(0e/0F)}{(0a/(0a/0B))} &= \frac{0F}{0B} = \left[\frac{0e/0L}{0e/0F} \right] \times \left[\frac{0e/(0e/0L)}{0a/(0a/0M)} \right] \times \left[\frac{0a/0B}{0a/0M} \right] \quad (8^{*'}) \\
&= (0F/0L) \times (0L/0M) \times (0M/0B) \\
&= (TC_r) \times (IC_r) \times (OC_r)
\end{aligned}$$

Decomposition of Change in Employment – TE_r , TC_r , IC_r , OC_r (Using period t and period $t+1$ as reference technologies)

In terms of Figure 2, equation (9) - the decomposition of the change in employment using period $t+1$ as the reference technology - can be expressed as:

$$\begin{aligned}
\frac{0e}{0a} &= \left[\frac{0e/0F}{0a/0B} \right] \left[\frac{0a/0B}{0a/0J} \right] \times \left[\frac{0e/(0e/0K)}{0a/(0a/0J)} \right] \times \left[\frac{0e/0K}{0e/0F} \right] \quad (9') \\
&= (TE_r) \times (TC_r) \times (IC_r) \times (OC_r)
\end{aligned}$$

Alternately, the change in employment can be decomposed using period t as the reference period for mixed-period LP problems which extends equation (8*):

$$\begin{aligned}
\Delta L_t^{t+1} &= \left[\frac{L^{t+1}}{L^t} \right] \quad (9^*) \\
&= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \\
&\quad \times \left[\frac{L^{t+1}/D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^t/D_i^t(x^t, L^t, y^t, b^t)} \right] \times \left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^t(x^t, L^t, y^t, b^t)} \right] \\
&= (TE_r) \times (TC_r) \times (IC_r) \times (M_r)
\end{aligned}$$

which in terms of Figure 2 can be written as:

$$\begin{aligned}
\frac{0e}{0a} &= \left[\frac{0e/0F}{0a/0B} \right] \times \left[\frac{0e/0L}{0e/0F} \right] \times \left[\frac{0e/(0e/0L)}{0a/(0a/0M)} \right] \times \left[\frac{0a/0B}{0a/0M} \right] \quad (9^{*'}) \\
&= (TE_r) \times (TC_r) \times (IC_r) \times (OC_r)
\end{aligned}$$

Decomposition of Change in Employment - – TE_r, TC_r, IC_r, OC_r (Geometric mean of using period t and period t+1 as reference technologies)

In order to avoid selecting an arbitrary reference technology, we take the geometric mean of equations (9) and (9*) to calculate the relative importance of factors associated with changes in employment. This yields the following expression:

$$\begin{aligned}
 \Delta L_t^{t+1} &= \left[\frac{L^{t+1}}{L^t} \right] \\
 &= \left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^t(x^t, L^t, y^t, b^t)} \right] \\
 &\quad \times \left[\left[\frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^{t+1}(x^t, L^t, y^t, b^t)} \times \frac{D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \right] \right]^{1/2} \\
 &\quad \times \left[\left[\frac{L^{t+1}/D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^t/D_i^{t+1}(x^t, L^t, y^t, b^t)} \times \frac{L^{t+1}/D_i^t(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})}{L^t/D_i^t(x^t, L^t, y^t, b^t)} \right] \right]^{1/2} \\
 &\quad \times \left[\left[\frac{D_i^{t+1}(x^{t+1}, L^{t+1}, y^t, b^t)}{D_i^{t+1}(x^{t+1}, L^{t+1}, y^{t+1}, b^{t+1})} \times \frac{D_i^t(x^t, L^t, y^t, b^t)}{D_i^t(x^t, L^t, y^{t+1}, b^{t+1})} \right] \right]^{1/2} \\
 &= (TE_r) \times (TC_r) \times (IC_r) \times (OC_r)
 \end{aligned} \tag{10}$$

In terms of Figure 2, equation (10) can be expressed as:

$$\begin{aligned}
 \frac{0e}{0a} &= \left[\frac{0e/0F}{0a/0B} \right] \times \left\{ \left[\frac{0a/0B}{0a/0J} \right] \times \left[\frac{0e/0L}{0e/0F} \right] \right\}^{1/2} \\
 &\quad \times \left\{ \left[\frac{0e/(0e/0K)}{0a/(0a/0J)} \right] \times \left[\frac{0e/(0e/0L)}{0a/(0a/0M)} \right] \right\}^{1/2} \times \left\{ \left[\frac{0e/0K}{0e/0F} \right] \times \left[\frac{0a/0B}{0a/0M} \right] \right\}^{1/2} \\
 &= (TE_r) \times (TC_r) \times (IC_r) \times (OC_r)
 \end{aligned} \tag{10'}$$

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Figure 1.
Unregulated and Regulated Isoquants (Cost Effect)

Figure 2.
Regulated Isoquants (Decomposition)

Table 1.**Summary Statistics (80 coal-fired power plants, 1995)**

	Units	Mean	Sample std. dev.	Maximum	Minimum
Electricity	kWh (in millions)	5,711	4,866	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	2,255
Heat content of oil	Btu (in billions)	109	116	514	0
Heat content of gas	Btu (in billions)	93	284	2,083	0
Summary Statistics (80 coal-fired power plants, 2005)					
	Units	Mean	Sample std. dev.	Maximum	Minimum
Electricity	kWh (in millions)	6,647	5,249	22,338	176
SO ₂	short tons (in thousands)	34	33	186	1
Capital stock	dollars (in millions, 1973\$)	329	227	1,000	59
Employees	workers	172	104	468	28
Heat content of coal	Btu (in billions)	66,877	51,036	215,802	2,297
Heat content of oil	Btu (in billions)	108	129	738	0
Heat content of gas	Btu (in billions)	71	157	911	0

Table 2

CE and Decomposition of L for Two-Year Pairs (Geometric Means for 80 coal-fired plants) (**BOLD** = maximum value and *ITALICS* = minimum value)

Two-year pairs	CE	L	TE _r	TC _r	IC _r	OC _r
1996–97	0.9991	0.9715	1.0032	0.9921	0.9494	1.0280
1997–98	0.9970	1.0009	1.0000	0.9967	0.9776	1.0273
1998–99	0.9994	0.9497	0.9961	1.0069	0.9368	1.0109
1999–00	1.0042	0.9769	0.9977	0.9992	0.9213	1.0636
2000–01	0.9995	1.0166	1.0081	0.9974	1.0958	0.9226
2001–02	1.0039	0.9793	0.9971	1.0016	0.9835	0.9970
2002–03	1.0023	0.9691	1.0165	0.9811	0.9282	1.0469
2003–04	1.0010	0.9884	0.9972	0.9974	1.0416	0.9541
2004–05	1.0000	1.0373	0.9973	1.0002	1.0044	1.0353
Annual (Geometric means)	1.0007	0.9874	1.0014	0.9969	0.9806	1.0086
Cumulative (Geometric means)	1.0063	0.8922	1.0127	0.9724	0.8384	1.0801

Note: Subtracting unity from values in Table 2 yield percentage changes.

Table 3

Geometric Means of 9 Two-year Pairs between 1996–97 and 2004–05 (**BOLD** = maximum value and *ITALICS* = minimum value)

Plant Name	Plant ID	CE	L	TE _r	TC _r	IC _r	OC _r
Barry	3	1.0000	0.9831	1.0009	0.9890	0.9768	1.0167
Gorgas	8	1.0000	0.9616	1.0010	0.9998	0.9745	0.9859
Colbert	47	1.0016	0.9939	1.0082	0.9983	0.9853	1.0022
Widows Creek	50	1.0015	0.9888	0.9958	0.9992	0.9783	1.0159
Cholla	113	1.0057	0.9545	0.9862	0.9959	0.9569	1.0156
Cherokee	469	1.0133	0.9806	0.9968	0.9839	0.9806	1.0195
Comanche	470	0.9956	1.0048	1.0075	0.9938	1.0222	0.9818
Valmont 5	477	1.0028	0.9981	0.9971	0.9971	1.0671	0.9408
Smith	643	1.0004	1.0342	0.9850	0.9988	1.0290	1.0216
Bowen	703	1.0000	0.9858	1.0000	0.9913	0.9987	0.9958
Hammond	708	1.0000	0.9919	0.9980	0.9990	0.9376	1.0611
Mitchell	727	1.0000	0.9891	0.9867	1.0001	0.9487	1.0567
Joppa Steam	887	0.9945	0.9802	1.0043	0.9893	0.9830	1.0036
Tanners Creek	988	1.0000	0.9806	1.0059	0.9991	0.9747	1.0011
Bailly	995	0.9944	0.9919	1.0128	0.9979	1.0686	<i>0.9185</i>
Cayuga	1001	1.0000	1.0000	0.9971	0.9999	0.9750	1.0287
R. Gallagher	1008	1.0000	1.0124	1.0031	0.9985	1.0029	1.0079
F.B. Culley	1012	0.9993	0.9926	1.0090	1.0073	0.9653	1.0118
M.L. Kapp	1048	1.0000	0.9973	0.9918	0.9902	0.9849	1.0311
Riverside	1081	1.0004	0.9966	1.0012	0.9837	0.9834	1.0290
LaCygne	1241	0.9999	0.9867	0.9959	0.9984	0.9874	1.0051
Big Sandy	1353	1.0000	0.9718	0.9987	0.9993	0.9526	1.0222
E.W. Brown	1355	1.0000	0.9875	1.0007	1.0011	0.9965	0.9891
Ghent	1356	1.0014	0.9671	0.9989	1.0001	0.9606	1.0077
Green River	1357	1.0000	0.9502	1.0066	0.9986	0.9505	0.9946
Cane Run	1363	1.0000	1.0042	1.0083	0.9893	0.9701	1.0377
Mill Creek	1364	1.0033	1.0466	0.9934	0.9960	1.0353	1.0217
Paradise	1378	1.0044	0.9882	1.0000	0.9946	0.9896	1.0040
Shawnee	1379	1.0074	0.9887	0.9923	1.0012	0.9756	1.0201
Monroe	1733	0.9997	0.9830	0.9982	0.9989	0.9910	0.9948
St. Clair	1743	1.0031	0.9809	1.0154	0.9828	0.9830	0.9999
High Bridge	1912	1.0048	0.9798	0.9976	0.9882	0.9669	1.0278
Asheville	2706	1.0000	1.0047	1.0124	0.9908	1.0154	0.9864
H.F. Lee	2709	1.0000	0.9984	1.0027	0.9985	0.9485	1.0513
L.V. Sutton	2713	1.0000	0.9887	1.0075	0.9985	0.9536	1.0305
G.G. Allen	2718	0.9997	1.0098	1.0024	0.9987	0.9834	1.0257
Buck	2720	1.0000	0.9799	1.0082	0.9984	0.9597	1.0144

Plant Name	Plant ID	CE	L	TE _r	TC _r	IC _r	OC _r
Cliffside	2721	1.0000	1.0074	1.0077	0.9988	0.9947	1.0062
Dan River	2723	1.0000	0.9953	1.0073	0.9988	1.0234	0.9667
Marshall	2727	1.0000	1.0111	1.0000	1.0004	1.0018	1.0089
Riverbend	2732	1.0000	1.0000	1.0040	0.9985	0.9913	1.0063
Muskingum River	2872	1.0000	0.9509	1.0026	0.9984	0.9616	0.9878
Lee	3264	1.0000	0.9971	1.0034	0.9985	0.9669	1.0292
McMeekin	3287	1.0000	0.9761	0.9967	0.9966	0.9632	1.0202
Watertree	3297	1.0000	1.0057	1.0032	0.9996	0.9791	1.0243
Williams	3298	1.0000	0.9972	0.9976	0.9984	0.9823	1.0192
Bull Run	3396	1.0000	0.9883	0.9991	0.9983	0.9618	1.0302
Cumberland	3399	1.0005	0.9953	1.0006	1.0022	1.0080	0.9847
Gallatin	3403	1.0056	0.9906	0.9974	1.0028	0.9692	1.0218
John Sevier	3405	1.0041	0.9962	1.0029	0.9980	1.0004	0.9949
Johnsonville	3406	1.0000	0.9931	1.0011	1.0010	0.9919	0.9990
Kingston	3407	1.0001	0.9763	1.0045	0.9988	0.9765	0.9965
Carbon	3644	0.9879	0.9867	1.0181	0.9947	0.9873	0.9868
Clinch River	3775	0.9991	0.9624	1.0045	0.9998	0.9720	0.9859
Glen Lyn	3776	1.0000	0.9673	1.0036	0.9985	0.9589	1.0067
Bremo Bluff	3796	1.0000	0.9970	1.0063	0.9987	0.9583	1.0352
Chesterfield	3797	1.0000	1.0010	1.0020	0.9985	0.9944	1.0061
Chesapeake	3803	1.0000	1.0025	1.0069	0.9988	0.9855	1.0115
Amos	3935	0.9997	0.9660	1.0024	0.9990	0.9428	1.0232
Kanawha River	3936	0.9999	0.9722	1.0028	0.9957	0.9650	1.0090
Sporn	3938	1.0000	0.9632	1.0026	0.9985	0.9770	0.9848
Rivesville	3945	1.0000	0.9076	1.0005	0.9985	0.8683	1.0464
Mount Storm	3954	1.0122	0.9939	0.9913	1.0011	0.9942	1.0075
Pulliam	4072	0.9976	1.0130	1.0168	0.9843	0.9838	1.0288
Weston	4078	0.9960	1.0022	0.9992	0.9915	0.9938	1.0178
Dave Johnston	4158	1.0169	0.9886	0.9821	1.0112	1.0031	0.9924
Naughton	4162	1.0000	0.9727	1.0015	0.9908	0.9765	1.0039
James H. Miller Jr.	6002	1.0058	0.9784	1.0014	0.9924	0.9681	1.0169
R.M. Schaffer	6085	0.9999	0.9680	1.0044	1.0068	0.9234	1.0366
A.B. Brown	6137	0.9989	0.9961	1.0106	0.9868	0.9727	1.0268
Welsh	6139	0.9947	1.0052	1.0025	1.0000	1.0020	1.0007
Harrington	6193	1.0035	0.9722	1.0000	0.9992	0.9774	0.9955
Tolk Station	6194	1.0006	0.9753	1.0000	0.9958	0.9805	0.9988
Pawnee	6248	0.9998	0.9935	1.0073	0.9893	0.9968	1.0003
Mountaineer	6264	1.0012	0.9797	0.9995	0.9986	0.9419	1.0421
Belews Creek	8042	1.0000	1.0077	1.0007	0.9989	0.9940	1.0142
Jim Bridger	8066	1.0010	0.9805	0.9985	0.9896	1.0021	0.9903

Plant Name	Plant ID	CE	L	TE _r	TC _r	IC _r	OC _r
Huntington	8069	0.9952	0.9866	1.0006	1.0078	0.9975	0.9809
General James M. Gavin	8102	1.0059	0.9537	0.9958	0.9977	1.0245	0.9370
Valmy	8224	1.0000	1.0011	1.0000	0.9994	0.9529	1.0511
Annual (Geometric means)		1.0007	0.9874	1.0014	0.9969	0.9806	1.0086

Note: Subtracting unity from values in Table 3 yield percentage changes.