Efficiency measurement when producers control pollutants: a non-parametric approach

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Abstract This paper treats efficiency measurement when some outputs are undesirable and producers control pollutants by end-of-pipe or change-in-process abatement. A data envelopment analysis framework that compares producers with similar pollution control efforts is proposed. First, my approach avoids arbitrary disposability assumptions for undesirable outputs. Second, the model is used to evaluate the interplay between pollution control activities and technical efficiency. I compare my approach to the traditional neo-classical production model that does not incorporate undesirable outputs among outputs, and to Färe et al.’s (Rev Econ Stat 71:90–98, 1989, J Econom 126:469–492, 2005) well-known model that incorporates bards. I evaluate the common assumption in the literature on polluting technologies, that inputs are allocatable to pollution control, and apply U.S. electricity data to illustrate my main point: Although my empirical model specifications are in line with the literature on polluting technologies, they rely on inputs that play an insignificant role in controlling nitrogen oxides (NOx) emissions. Consequently, there are no reasons to expect the efficiency scores of the traditional model to differ from the efficiency scores of the other two models that account for resources employed to pollution control. Statistical tests show that my model, which explicitly takes pollution control efforts into account, produces efficiency scores that are not statistically different from the traditional model’s scores for all model specifications, while Färe et al.’s model produces significantly different results for some model specifications. I conclude that the popular production models that incorporate undesirable outputs may not be applicable to all cases involving polluting production and that more emphasis on appropriate empirical specifications is needed.

Keywords Data envelopment analysis · Directional output distance function · Pollution control · Allocatable inputs · Weak disposability axiom

JEL Classification D24 · Q52 · C61

1 Introduction

In recent years, there has been increasing concerns for treating undesirable outputs in the production analysis literature. A debate about which axioms are suitable when some outputs are undesirable has emerged correspondingly: First, if pollutants are modeled as freely disposable inputs [or costly disposable outputs (Murty 2010)], then the generation of emissions is assumed to be unbounded (Färe and Grosskopf 2003). Second, if pollutants are modeled as freely disposable outputs, then the generation of emissions can be avoided at no costs (Färe and Grosskopf 2003). Second, if pollutants are modeled as freely disposable outputs, then the generation of emissions can be avoided at no costs (Färe and Grosskopf 2003). To overcome these conceptual problems, Färe et al. (1989, 2005) suggest modeling pollutants as weakly disposable outputs (Shephard 1970). This approach is criticized for being inconsistent with the materials balance condition (Coelli et al. 2007) and for not capturing the wide range of options that producers have for reducing undesirable outputs (Förrsund 2009).

The current paper suggests a simple way to avoid the issue of selecting appropriate axioms for undesirable outputs, namely by not including undesirable outputs in the production model. However, I recognize that pollution control activities may take place at the expense of desirable
outputs. I therefore allow production possibilities for desirable outputs to depend on pollution control efforts by restricting the comparisons of decision making units to those with similar control efforts. My approach is comparable to Färe et al.’s (1989, 2005) approach to modeling joint production of desirable and undesirable outputs, since the latter attributes reductions in pollutants to “the imposition of a fine, or more likely in the present case through diversion of given inputs to cleanup of the bad output” (Färe et al. 2005, p. 472). In fact, it can be shown that emission reduction by pollution control is required to make the underlying axioms of Färe et al.’s model consistent with physical constraints on the conversion of inputs into outputs, i.e. with the materials balance condition (Rødseth 2011). Pollution control efforts are, however, not explicitly considered by Färe et al.’s model, which makes it interesting to compare their approach to my approach that explicitly takes pollution control into account. I show that my model, unlike Färe et al.’s model, avoids negative trade-offs between desirable and undesirable outputs—an issue that has been brought up in the literature on pollution control technologies; see Førsund (2009) and Picazo-Tadeo and Prior (2009).

The relationship between environmental regulations and productivity has received much attention in the environmental economics literature. The pioneering literature in this field relied on traditional measures of productivity that evaluate the relationship between inputs and desirable outputs. See e.g. Jaffe et al. (1995) for an overview. Several recent papers, e.g. Chung et al. (1997), Färe et al. (2001, 2007b), and Ball et al. (2005), criticize the early studies for not considering inputs applied to pollution control productive since efforts to reduce emissions are not accounted for by traditional productivity analysis. To circumvent this measurement problem, they suggest applying the model of Färe et al. (1989, 2005) to credit producers for the resources they use for pollution control purposes. Although pollution control activities are not explicitly modeled, the underlying (but implicit) assumption is that inputs are allocatable to pollution control and that some desirable outputs must be forgone when inputs are diverted from intended production to cleanup of pollutants. Hence, producers who allocate resources to pollution control are likely to be considered relatively more technical efficient by Färe et al.’s model than by the traditional production model.

Studies on polluting technologies do usually include little discussion about whether inputs used for empirical assessments really are allocatable to pollution control. Clearly, if they are not, then there are no reasons to expect models which credit pollution control activities to produce efficiency scores that are significantly different from the efficiency scores of the traditional production model. I apply a dataset consisting of 54 American power plants that produce electricity jointly with NO$\textsubscript{x}$ to illustrate this point. In line with the literature on polluting technologies I consider fuels, generating capacity, and labor as inputs. With a possible exception for labor, these inputs cannot be considered allocatable to pollution control activities for NO$\textsubscript{x}$. My hypothesis is therefore that the efficiency scores of the traditional production model will not be statistically different from the efficiency scores of my model or Färe et al.’s model. I apply data envelopment analysis (DEA) to calculate the efficiency scores and use a battery of statistical tests to compare the three models. I find that the efficiency scores of the traditional model and my model are not significantly different from each other for all model specifications considered. A similar result is not obtained when comparing the traditional model to Färe et al.’s model.

This paper is structured as follows. The following section includes a discussion on pollution control and the assumption of allocatable inputs. Section 3 provides a theoretical overview of the three production models considered in this paper, while Sect. 4 discusses the dataset and the empirical implementation. Section 5 summarizes the results of my empirical inquiry, while Sect. 6 concludes.

2 Pollution control activities and their implications for efficiency measurement

Physical limits to production, in particular the first and second laws of thermodynamics, imply that byproducts are unavoidable when desirable or intended outputs are being produced (Baumgärtner and Arons 2003; Baumgärtner et al. 2001).

When considering the underlying dynamics of pollution generation and reduction, it is convenient to introduce the concepts of uncontrolled (before pollution control) and controlled (after pollution control) emissions. Starting with the uncontrolled emissions, I assume that they can be represented by emission and recuperation factors. These factors relate the quantity of an undesirable byproduct released into the environment to certain activities, e.g. relate tons of NO$\textsubscript{x}$ emitted to the amount of fossil fuels used for combustion. Let $x \in \mathbb{R}_{+}^{K}$ denote a vector of inputs, $y \in \mathbb{R}_{+}^{M}$ denote a vector of desirable outputs, and $b \in \mathbb{R}_{+}^{L}$ denote a vector of byproducts or undesirable outputs. Further, let $U$ be a $(K \times N)$ matrix of emission factors and let $V$ be a $(K \times M)$ matrix of recuperation factors for the

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$^1$ This approach has become popular in research that integrate the materials balance condition in microeconomic production analysis; see e.g. Coelli et al. (2007) and Lauwers (2009).
desirable outputs, and define the uncontrolled emissions for the \( K \) undesirable outputs as:

\[
b = Ux - Vy
\]  

Equation 1 suggests that there are several ways to reduce undesirable outputs. First, a proportional reduction in inputs, i.e. in the scale of operations, will lead to reduced by-production. Second, substituting inputs which emission factors are relatively high with inputs which emission factors are relatively low has positive environmental effects. One example is to replace coal with gas in fossil fuel fired electricity plants, since combustion with gas contributes to substantially less air pollution than coal. Similarly, substituting low-recuperating outputs with high-recuperating outputs reduces uncontrolled emissions. Third, efficiency improvements and productivity growth that increase the ratio between desirable outputs and inputs will equally contribute to a decline in the production’s environmental impact.

Output reductions, input and output substitution, and technical change reduce (or prevent) the generation of \( b \) directly, i.e. they reduce uncontrolled emissions. However, these options may be costly for producers that are facing requirements to reduce emissions. An alternative is therefore to comply with environmental regulations by reducing \( b \) indirectly, by “cleaning up” emissions instead of preventing them from occurring. This type of cleaning activity is called pollution control and encompasses various types of change-in-process abatement and end-of-pipe abatement. The widespread use of equipments that remove sulfur and nitrogen emissions from flue gases in power plants is an example of pollution control. It allows the power producers to avoid (possibly) costly fuel substitutions, but still to comply with the environmental regulations they face.

Let \( a \in \mathbb{R}^K \) be the vector of pollution control efforts. It may for example measure tons of air pollutants which are removed from flue gases. The emissions released to the environment after pollution control, i.e. the controlled emissions, may then be defined as:

\[
b = Ux - Vy - a
\]  

Pollution control activities are important in the literature on polluting technologies. I identify two underlying, though often implicit, assumptions that are connected to these activities:

1. Inputs that are employed to pollution control (may) cause biases in traditional measures of technical efficiency.
2. At least one of the inputs applied in empirical model specifications of polluting technologies is allocatable to pollution control.

The first assumption suggests that pollution control activities cause problems with traditional measures of technical efficiency that concern conversion of inputs into desirable outputs: when inputs applied to pollution control are used in empirical efficiency analyses that emphasize the efficiency in which inputs are converted into desirable outputs, decision making units that employ much resources to pollution control will be considered inefficient compared to decision making units that employ less resources to pollution control since “pollution control inputs” do not contribute to the production of desirable outputs. In other words, inputs applied to pollution control are assumed to be unproductive because the producers’ efforts to reduce emissions are not accounted for (Färe et al. 2001). This point is widely accepted in the literature on polluting technologies and has lead to a new branch of “environmentally adjusted” productivity measures. See for example Chung et al. (1997), Färe et al. (2001, 2007b), and Ball et al. (2005) for more details. None of the mentioned studies do, however, explicitly model reductions in undesirable outputs by pollution control. Emission reductions more or less take place “behind the scene.” As will be shown in Sect. 3.2, the model underlying these analyses, the model of Färe et al. (1989, 2005), clearly attributes reductions in undesirable outputs to pollution control activities.

Färe et al.’s model’s attribution of emission reductions to pollution control activities leads to the second assumption, which states that at least one of the inputs applied in empirical analyses is allocatable to pollution control activities. I would like to stress that there have not been much effort to identify and separate inputs that go into pollution control processes from inputs used to produce desirable outputs in empirical studies that follow Färe et al.’s modeling approach. In fact, pollution control and other strategies for reducing emissions are rarely mentioned. In a recent treatment on polluting technologies, Førsund (2009) assumes that pollution control inputs differ from the inputs that go into the production of desirable outputs. While Førsund (2009, p. 29) “do(es) not assume that purification (i.e. pollution control) inputs are used at the expense of production inputs”, the underlying idea behind Färe et al.’s model is that pollution control takes place “…through diversion of given inputs to cleanup of the bad output” (Färe et al. 2005, p. 472), for a given input vector. A similar argument can be found in studies that

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Footnotes:

1. The widespread use of equipments that remove sulfur and nitrogen emissions from flue gases in power plants is an example of pollution control. It allows the power producers to avoid (possibly) costly fuel substitutions, but still to comply with the environmental regulations they face.

2. End-of-pipe abatement involves production processes that transform uncontrolled byproducts into different byproducts that are of less threat to the environment. One of the issues with end-of-pipe abatement is that it causes additional byproducts, since the abatement process itself is also subordinate to the laws of physics. This issue will not be treated further in the current article; see Pethig (2006) for a discussion.
model undesirable outputs as if they are freely disposable inputs; see e.g. Barbera and McConnell (1990). Shadbegian and Gray (2005) deal with this issue explicitly by separating capital, labor, and materials used for pollution control and production of desirable outputs, respectively. To my knowledge, such considerations are not taken in empirical studies that apply Färe et al.’s (1989, 2005) model.3

Two aspects must be brought up in connection to the two assumptions about pollution control:

(a) Equations 1 and 2 indicate that producers have several options for complying with environmental regulations, i.e. output reductions, input and output substitution, technical change, and pollution control activities. The problem of “unproductive pollution control inputs” does only apply to pollution control activities, and not to the other alternatives. For example, cases with regulatory induced input substitution cause measurement bias for allocative efficiency rather than having implications for the measurement of technical efficiency. This issue is treated further in Rødseth (2013). In summary, the popular models that incorporate desirable and undesirable outputs are perhaps most suitable for regulated industries with a widespread adoption of pollution control.

(b) If empirical studies on polluting technologies rely on inputs that have no relevance for pollution control activities, then the problem of “unproductive pollution control inputs” is no longer relevant and should not be identifiable in “environmentally adjusted” efficiency analyses. The current paper deals with this issue.

3 Theoretical underpinnings

3.1 The traditional production model

Let us start with the notion of a technology that converts inputs into outputs. Let \( P(x) \) be the set of feasible or achievable outputs, defined for all \( x \) in \( \mathbb{R}^N_+ \). In the following I introduce three different production models, each represented by their respective output sets. I use superscripts \( T, W, \) and \( A \) to distinguish the models, where \( T \) refers to the traditional production model, \( W \) refers to Färe et al.’s (2005) model, and \( A \) refers my model. For example, the output sets of the traditional production model are for each input vector \( x \) defined by:

\[
P^T(x) = \{y : x \text{ can produce } y\}
\]

The properties of the output sets are introduced in the form of axioms. For the traditional production model, the standard axioms of no free lunch and inactivity, compact and convex output sets, and free disposability of inputs and desirable outputs are assumed to apply. These properties are described in more detail in Färe and Primont (1995).

The traditional production model does not account for the generation of undesirable outputs (as well as their reductions). One may expect that emission reductions take place at the expense of desirable outputs for given inputs. The discussion in Sect. 2 suggests that this is the case when emissions are reduced by pollution control. In that case, production possibilities for desirable outputs should depend on pollution control efforts. In the following, I present two models that attempt to deal with this issue.

3.2 The weak disposability model

This section provides a short summary of the model framework of Färe et al. (2005). Let \( B^W(x) \) be an output set containing desirable and undesirable outputs:

\[
P^W(x) = \{(y,b) : x \text{ can produce } (y,b)\}
\]

With the exception of free disposability of undesirable outputs, Färe et al. (2005) impose the axioms of the traditional production model on the output set from Eq. 4. Two non-conventional axioms are also added to capture that some of the outputs are undesirable:

(i) if \((y,b) \in P^W(x)\) and \(b = 0\), then \(y = 0\)
(ii) if \((y,b) \in P^W(x)\) and \(0 \leq \theta \leq 1\), then \((\theta y, \theta b) \in P^W(x)\)

Axiom (i), null-jointness (Shephard and Färe 1974), implies that undesirable outputs are unavoidable when desirable outputs are being produced. Axiom (ii) is known as weak disposability of desirable and undesirable outputs. It implies that proportional output reductions always are feasible. This axiom allows modeling costly emission reductions since desirable outputs must be forgone to reduce undesirable outputs. The model thereby considers inputs used for reducing emissions productive.\(^4\)

Using Eq. 2 (controlled emissions) together with axiom (ii), it is straightforward to show that the weak disposability axiom suggests that emission reductions take place by pollution control (Rødseth 2011):

\(^3\) Recently, some authors have applied Network DEA (Färe and Grosskopf, 2000) to model pollution control activities explicitly (Färe et al. 2013; Hampf, 2013). These studies determine which inputs are allocatable to the production of desirable outputs and pollution control.

\(^4\) The weak disposability model does however not rule out regions of the outputs sets where undesirable outputs can be reduced while simultaneously increasing desirable outputs.
\[ \theta[b + vy] = ux - a \] (5)

The weak disposability axiom suggests that a proportional contraction of y and b is always feasible for given inputs, x. Assume first that pollution control activities do not take place, i.e. the pollution control vector in Eq. 5 is the zero vector. It follows readily that the only solution to Eq. 5 (the representation of controlled emissions) is \( \theta = 1 \) for given x. That is, a proportional contraction of y and b (i.e. the weak disposability axiom) is not physically attainable for given x. However, pollution control efforts resolve this problem. Whenever they can be increased by \((1 - \theta)(b + vy)\) for given inputs, pollution control counteracts the proportional contraction of y and b and thereby allows Eq. 5 to hold with equality. In other words, Färe et al.'s (1989, 2005) model implicitly assumes that emission reductions take place by pollution control. The costs of environmental regulations should therefore be viewed in terms of inputs allocated to pollution control activities.

3.3 The pollution control model

I now present an alternative approach to modeling polluting technologies, building on Ruggiero’s (1996) model for evaluating contextual factors’ impact on technical efficiency in the public sector. I do not model undesirable outputs directly as a part of the technology, but consider environmental regulations and, thus, pollution control efforts as contextual variables that possibly influence the relative performance of producers.

Similar to Färe et al. (1989, 2005), I assume that increases in pollution control efforts may take place at the expense of desirable outputs for a given input vector. I apply the output set from Eq. 3 as my point of departure, but make it conditional on pollution control efforts:

\[ P^A(x; a^1) \subseteq P^A(x; a^2) \text{ if } a^1 \geq a^2 \] (7)

In O’Donnell et al. (2008), the meta technology is defined by the union of group-technologies. In my case, the output sets for \( a^1 \) is included in the output sets for \( a^2 \) which means that the union of the two sets is equivalent to \( P^A(x; a^2) \). Put differently, when pollution control efforts are lowered, more of the meta technology from Eq. 3 becomes available. Since there is a lower bound to pollution control efforts (namely zero), it follows readily that \( P^A(x; 0) = P^A(x) \).

Clearly, my model accommodates the possibility that some desirable outputs must be forgone in order to reduce emissions by pollution control since production possibilities for desirable outputs are allowed to depend on pollution control. Notice, however, that any controversial axiom for undesirable outputs is avoided.

Contrary to the literature reviewed in Sect. 3.2, a few recent contributions on polluting technologies deal explicitly with (1) identifying inputs that contribute to emission generation and (2) modeling pollution control (Førsund 2009; Murty et al. 2012; Pethig 2006). The three studies differ in terms of their treatment on pollution control, with Murty et al. (2012) assuming that inputs are allocatable to pollution control and desirable outputs, Pethig (2006) assuming that pollution control and desirable products are non-joint in inputs, and Førsund (2009) assuming that production inputs will not (or cannot) be allocated to pollution control and vice versa. In other words, the three studies impose specific relationships between inputs, desirable outputs, and pollution control \( a \) priori. I therefore do not consider them suitable for the purpose of empirical testing of whether certain inputs (fuels, labor, and generating capacity) play a role in pollution control. Instead of explicitly modeling pollution control technologies the production model in Eq. 6 treats pollution control as a contextual variable that possibly affects producers’ performance. In principle, my model can be considered as an alternative approach to the well-known two-stage DEA (Ray 1988), which has been extensively used to identify the impact of contextual variables on technical efficiency. Note that my model is not vulnerable to the critique of the two stage DEA; see Simar and Wilson (2007, p. 36).

3.4 Function representations

A function representation is required to apply the three technology specifications from Eqs. 3, 4, and 6 for empirical analysis. I consider the directional output distance function (Chung et al. 1997) suitable for this purpose. I do not measure performance by expanding desirable outputs and contracting undesirable outputs, which is
common in the literature; see e.g. Färe et al. (2005) and Murty et al. (2012). The reason is that the traditional model and my model do not incorporate undesirable outputs, and the efficiency evaluations would therefore not be comparable across the three models. Instead, performance is evaluated by expanding desirable outputs to the technology frontier. Let \( g_s \) be a direction vector in \( \mathbb{R}^M \), and define directional output distance functions for the three technologies:

\[
\begin{align*}
\bar{D}_O^T(x, y; g_s) &= \max \{ \beta^T : (y + \beta^T g_s) \in P^T(x) \} \\
\bar{D}_O^A(x, y; a, g_s) &= \max \{ \beta^A : (y + \beta^A g_s) \in P^A(x; a) \} \\
\bar{D}_O^W(x, y; b; g_s, 0) &= \max \{ \beta^W : (y + \beta^W g_s, b) \in P^W(x) \}
\end{align*}
\]  

(8)

The directional distance function inherits the properties of the parent technology and provides a complete characterization of the technology. That is,

\[
\begin{align*}
y \in P^T(x) \text{ if and only if } \bar{D}_O^T(x, y; g_s) &\geq 0 \\
y \in P^A(x; a) \text{ if and only if } \bar{D}_O^A(x, y; a, g_s) &\geq 0 \\
y \in P^W(x) \text{ if and only if } \bar{D}_O^W(x, y; b; g_s, 0) &\geq 0
\end{align*}
\]  

(9)

It further satisfies the translation property, is non-increasing and concave in \( y \), and homogeneous of degree minus one in \( g \).

It follows readily from Eq. 9 and (the discussion following) Eq. 7 that:

\[
\bar{D}_O^T(x, y; g_s) \geq \bar{D}_O^A(x, y; a, g_s)
\]  

(10)

Clearly, when production possibilities for desirable outputs are reduced as a result of pollution control efforts, the distance to the frontier of the output set must be reduced correspondingly. In terms of efficiency evaluations, this result implies that producers who reduce their emissions by pollution control are not “punished” by the pollution control model for doing so: whenever the producers’ pollution control efforts increase for given inputs, their performance evaluations improve correspondingly. The traditional production model from Eq. 3 may, on the contrary, perceive abating producers as inefficient in cases where they are allocated at the frontier of the group output sets of the pollution control model from Eq. 6.

Similar to the pollution control model, the producers are considered at least as efficient by the weak disposability model as by the traditional production model. There is, however, no clear relationship between the weak disposability model and the pollution control model. Figure 1 provides an explanation:

Figure 1 illustrates the output sets for the three technologies, \( P^T(x) \), \( P^W(x) \), and \( P^A(x; a) \), assuming piecewise-linear technologies for four producers (A, B, C, and D) that apply the similar input vector to produce one desirable output, \( y \), and one undesirable output, \( b \). A crucial point for understanding the figure is to recognize that producers located to the left in the figure display the highest pollution control efforts. I derive this conclusion by applying the representation of controlled emissions in Eq. 2, assuming that there are no recuperation of undesirable outputs in intended products. This corresponds to the case of air pollution emissions from power plants, the case to be treated in Sects. 4 and 5. Since the input vector is assumed to be fixed for the output set, the only way to reduce the undesirable output, \( b \), is by pollution control; see Sect. 2. This means that producer D displays lower pollution control efforts (\( a^1 \)) compared to producer A, while producer B displays higher pollution control efforts (\( a^2 \)) compared to producer C.

The traditional production model does not take undesirable outputs into account, but is only concerned with estimating production possibilities for desirable outputs. Hence, the maximal feasible amount of desirable output, \( y^R \), makes up the frontier of the output set of the traditional production model, \( P^T(x) \). When evaluating performance relative to this frontier, it follows that producers A, D, and C are inefficient since their supply of the desirable output is less than producer B’s supply—despite the higher pollution control efforts of producers A and D relative to producer B.

The model of Färe et al. (1989, 2005) is represented by the output set bounded by \( 0ABCE0 \). The weak disposability assumption does, with the exception of the line segments BC and CE, lead to a positive trade-off between the desirable and undesirable output, implying that some desirable output must be forgone in order to reduce the undesirable output when a producer is allocated at the frontier of the output set. Applying the directional output distance function that projects all observations to the frontier in the direction of the desirable output (i.e. by increasing \( y \), Färe et al.’s technology considers producers A, B, and C efficient. Producer D is allocated in the interior of the weakly disposable output set.

Finally, the pollution control model estimates production possibilities for the desirable output, contingent on
pollution control efforts. Consider producer D with pollution control efforts \(a^D\). From Fig. 1, it is clear that only one producer, A, displays a higher pollution control effort than producer D. The pollution control model will therefore only compare the performance of producer D (in terms of expansions of desirable outputs) to the performance of producer A. Since producer D’s desirable output, \(y^D\), is slightly higher than producer A’s output, producer D is considered technical efficient by the pollution control model. Next, consider producer B. It is clear that its peers, producers A and D, display higher pollution control efforts than producer B, but producer B’s output, \(y^B\), by far exceeds \(y^O\). Producer B is therefore also considered efficient. Producer C’s pollution control efforts and production of the desirable output are, on the other hand, lower than those of producer B. Producer C is therefore considered inefficient by the pollution control model. In summary, producers A, B and D are considered to be technical efficient by the pollution control model.

Comparing the three models, it is clear that they differ in terms of assigning efficient decision making units. The traditional production model puts no weight on pollution control efforts and therefore only considers producer B to be efficient. The weak disposability model and the pollution control model account for efforts to reduce emissions when evaluating performance, but they rank producers differently. While the weak disposability model considers producers A, B and C technical efficient, the pollution control technology considers producers A, B, and D technical efficient. The weakly disposable technology includes the convex combination of the output vectors of producers A and B, which immediately means that producer D is allocated in the interior of its output set. The pollution control technology does, on the other hand, resemble a free disposable hull and therefore allows producer D to be allocated on the frontier of the group output set. Next, producer C is allocated on the frontier of the weakly disposable technology, but in the interior of the pollution control technology. The latter result is simply due to the fact that producer B’s pollution control efforts and production of the desirable output by far exceed that of producer C. In terms of the weakly disposable technology, producer C is located in a region of the production frontier with a negative trade-off between the desirable and undesirable outputs. This means that the undesirable output can be reduced while simultaneously increasing the desirable output, i.e. pollution reduction is profitable. This is a counterintuitive result that contradicts classical environmental economics. The existence of negatively sloped regions of the output set is therefore often considered a shortcoming of the weakly disposable technology (Førsund 2009; Picazo-Tadeo and Prior 2009).

This issue is, however, avoided by the pollution control technology.\(^5\)

4 Dataset and empirical implementation

I estimate the directional output distance functions from Eq. 8 by activity analysis or DEA, using a dataset which includes 54 U.S. electricity plants that operate in 2005. All units face legal restrictions on air pollution emissions. The current study is concerned with control efforts for air pollution that are induced by existing regulations. More specific, NOx is considered to be an undesirable output that is produced jointly with electricity,\(^6\) and pollution control for NOx is considered to have a possible negative impact on the plants’ performance (in terms of electricity generation). There are primarily two approaches to controlling NOx emissions that have been adopted by U.S. power plants: combustion controls (e.g. low NOx-burners that control fuel and air mixing to reduce peak flame temperature) and end-of-pipe technologies (Selective Catalytic Reduction and Selective Non-Catalytic Reductions) that remove NOx emissions from flue gases.

In line with other studies on undesirable outputs in electricity generation (e.g. Färe et al. 2005, 2007a; Pasurka 2006), I assume that the power plants consume fossil fuels, capital (approximated by generating capacity), and labor. These inputs are strongly related to the desirable output (electricity) but appear to be less related to the previously described approaches to control NOx emissions, in particular to combustion controls. First, pollution control for NOx requires capital investments that are additional to investments in generating capacity. Second, although pollution control may require energy inputs, fossil fuels cannot be considered allocatable to pollution control. In fact, combustion of fossil fuels is the primary source of NOx emissions and thus the reason for pollution control. However, since labor efforts play a role in operations and maintenance of NOx controls it is possible to consider labor as an allocatable input that can be used both for electricity generation and pollution control.

\(^5\) One referee pointed out that the issue of negative shadow prices can also be resolved by assuming that pollutants are freely disposable inputs (or costly disposable outputs). This approach to modeling undesirable outputs is explored by Hailu and Veeman (2001), but has been criticized by Färe and Grosskopf (2003) for being inconsistent with physical laws.

\(^6\) The power plants face regulation on both nitrogen and sulfur emissions. The regulations on sulfur emissions involve emissions trading, while the regulations on nitrogen to a larger extent are based on emission standards. In Rodseth (2011), emissions trading and pollution control are viewed as substitutes that may both be applied to increase the production of desirable outputs without violating legal emission constraints. Since the current paper is concerned with resources allocated to pollution control I choose to focus on nitrogen control, to avoid considerations between pollution control and emissions trading.
My dataset is a revision of Rødseth’s (2011) dataset that focuses on substitution among coal and natural gas. The reason for this emphasis is that combustion with coal (and oil) leads to a higher formation of air pollution emissions than natural gas firing. To model a homogeneous production technology I follow Welch and Barnum (2009) and only include plants that obtain at least 1 percent of their energy inputs from both coal and gas,7 in addition to following Färe et al. (2007b) by excluding plants for which more than 0.0001 percent of the energy inputs come from other sources than fossil fuels. Most of the plants that satisfy these criteria have a negligible consumption of petroleum fuels. To avoid zeros in the input data, I do not consider coal, gas, and petroleum separately, but aggregate the heat content (mmBTUs) of coal and petroleum into one input (the “high-polluting” fuel) that is consumed together with natural gas (the “low-polluting” fuel).

EIA-906/920 provides monthly information on fuel consumption and net generation of electricity. I aggregate this information up to annual consumption and generation for each plant. Information about the plants’ generating capacity is obtained from EIA statistics on capacity. The form FERC 1 provides information about the average number of workers at the plants. Unfortunately, labor data is only available for 26 of the 54 plants in the dataset. A major problem with excluding plants that do not report labor from the sample is that the following reduction in sample size reduces the ability to discriminate among power plants. I therefore apply a method developed by Kuosmanen (2009) that handles missing data in DEA. Kuosmanen suggests replacing missing input values by a “sufficiently large number”, such that the shadow price on the labor constraint is zero for all plants with missing labor data (i.e. such that the missing input is effectively excluded from the analysis when evaluating the efficiency of plants with missing data). I consider a wide range of possible “large numbers” for the missing labor values and conclude that 7.00E+10 is sufficient to satisfy Kuosmanen’s criterion. Second, I estimate the production models with and without labor to consider whether labor, the only input considered that possibly can be allocated to both electricity and pollution control, affects the differences in efficiency of plants with missing data. I therefore apply a method developed by Kuosmanen (2009) that handles missing data in DEA. Kuosmanen suggests replacing missing input values by a “sufficiently large number”, such that the shadow price on the labor constraint is zero for all plants with missing labor data (i.e. such that the missing input is effectively excluded from the analysis when evaluating the efficiency of plants with missing data). I consider a wide range of possible “large numbers” for the missing labor values and conclude that 7.00E+10 is sufficient to satisfy Kuosmanen’s criterion. Second, I estimate the production models with and without labor to consider whether labor, the only input considered that possibly can be allocated to both electricity generation and pollution control, affects the differences between the two production models that take pollution control efforts into account and the traditional production model.

The form EIA-767 (boiler) provides information on the total number of hours NOx control was in service during 2005. I consider this variable to be a suitable proxy for the plants’ efforts to control NOx emissions. Other available measures could also be used, but I consider them to be less reliable. For example, EIA-767 provides information on the average annual NOx removal rate. The removal rate depends on the design of the generating utility and the pollution control equipment, which means that parameters such as boiler type and size that are not directly related to the resources employed to pollution control play an important role in determining NOx removal. Alternatively, the amount of NOx removed by pollution control can be calculated by estimating uncontrolled emissions (by applying emission factors reported in the appendices of EIA’s Electric Power Annual) and subtracting controlled emissions (which are reported by Environmental Protection Agency’s (EPA) Clean Air Markets database). The problem with this approach is that any errors in the estimates of uncontrolled emissions result in biased estimates of pollution control. Hence, I consider the number of hours of NOx control to be the preferable proxy for resources employed to pollution control. The dataset is summarized by Table 1.

I apply the dataset to estimate the directional output distance functions from Eq. 8, using DEA. Assume that there are \( l = 1, \ldots, L \) electricity plants in the dataset. Each plant consumes fossil fuels, capital, and labor, \( x_l = (x_{l1}, \ldots, x_{l4}) \in \mathbb{R}^4_+ \), to produce electricity \( y_l \in \mathbb{R}_+ \). Let \( \lambda^l, l = 1, \ldots, L \), be the intensity variables, and let the direction vector \( g^l \) be equal to each plant’s electricity output. For plant \( l \), the empirical counterpart to the directional output distance function for the traditional production model is then defined by:

\[
\tilde{D}^T_l(x^l, y^l; g^l) = \max \beta^T : \sum_{l=1}^L \beta^T y^l - \sum_{l=1}^L \beta^T x^l_n, \ n = 1, \ldots, 4 \quad \lambda^l \geq 0, \ l = 1, \ldots, L \quad (11)
\]

Equation 11 does not include a summing-up restriction on the intensity variables, which means that the LP program computes the constant returns to scale (CRS) DEA model. Next, I consider the empirical counterpart to the pollution control model. Let pollution control efforts for NOx be denoted \( d^l \in \mathbb{R}_+ \), and consider:

\[
\tilde{D}^A_l(x^l, y^l; d^l; g^l) = \max \beta^A : \sum_{l=1}^L \beta^A y^l + \beta^A \lambda^l \quad \sum_{l=1}^L \beta^A x^l_n 
\leq \sum_{l=1}^L \beta^A x^l_n, n = 1, \ldots, 4 \quad \lambda^l \geq 0, \ \forall l : d^l \geq d^l' \quad \lambda^l = 0, \ \forall l : d^l < d^l' \quad (12)
\]

The first five constraints in Eq. 12 are standard (and equal to the first five constraints in Eq. 11), while the

7 The original dataset is collected for the period 2002–2009 and has been updated for 2002–2005. It uses a modified selection criterion, namely that the plants must satisfy Welch and Barnum’s criterion in 2002 and have nonzero consumption of coal and gas in the following years. Consequentially, some of the plants in the sample may violate Welch and Barnum’s criterion in 2005. Historical information does, however, show that the plants in the sample have gas capacities that allow them to satisfy the selection criterion.
Table 1  Summary statistics (54 plants)

| Variable                  | Mean     | Std.Dev  | Min     | Max        |
|---------------------------|----------|----------|---------|------------|
| High-polluting fuel (mmBTU) | 32,129,290.0 | 26,575,532.0 | 1,438,240.0 | 121,000,000.0 |
| Low-polluting fuel (mmBTU)   | 2,810,866.0  | 5,928,644.0  | 16,568.5 | 32,800,000.0 |
| Capacity (MW)              | 807.0     | 613.4     | 31.9    | 2,671.4    |
| Labor^a (workers)          | 140.8     | 74.4      | 16.0    | 286.0      |
| Electricity (MwH)          | 3,324,180.0 | 2,965,044.0 | 137,760.0 | 14,600,000.0 |
| Nitrogen (t)               | 5,515.1    | 4,376.1    | 326.9   | 19,248.5   |
| Pollution control (h)      | 14,782.1   | 11,291.6   | 0.0     | 56,187.0   |

^a Summary statistics for labor only concerns the 26 plants for which number of workers is reported.
Table 2 Efficiency scores

| Plant               | Traditional Without labor | Traditional With labor | Pollution control Without labor | Pollution control With labor | Weak disposable Without labor | Weak disposable With labor |
|---------------------|---------------------------|------------------------|--------------------------------|------------------------------|-------------------------------|----------------------------|
| Barry               | 0.021                     | 0.000                  | 0.000                          | 0.000                        | 0.006                         | 0.000                      |
| Green County        | 0.066                     | 0.027                  | 0.000                          | 0.000                        | 0.053                         | 0.018                      |
| Apache S.           | 0.127                     | 0.127                  | 0.055                          | 0.055                        | 0.069                         | 0.068                      |
| Arapahoe            | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Cameo               | 0.007                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Cherokee            | 0.008                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Martin Drake        | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Crist               | 0.108                     | 0.000                  | 0.000                          | 0.000                        | 0.089                         | 0.000                      |
| Lansing Smith       | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Deerhaven G.S       | 0.187                     | 0.153                  | 0.187                          | 0.153                        | 0.166                         | 0.152                      |
| C.D. McIntosh       | 0.067                     | 0.067                  | 0.067                          | 0.067                        | 0.055                         | 0.055                      |
| Jack McDonough      | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Yates               | 0.096                     | 0.073                  | 0.000                          | 0.000                        | 0.080                         | 0.071                      |
| Kraft               | 0.236                     | 0.236                  | 0.236                          | 0.236                        | 0.202                         | 0.202                      |
| Harding Street      | 0.096                     | 0.096                  | 0.019                          | 0.019                        | 0.095                         | 0.095                      |
| Sutherland          | 0.145                     | 0.137                  | 0.145                          | 0.137                        | 0.000                         | 0.000                      |
| Riverside           | 0.319                     | 0.319                  | 0.319                          | 0.319                        | 0.215                         | 0.215                      |
| Muscatine #1        | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Riverton            | 0.358                     | 0.269                  | 0.357                          | 0.261                        | 0.298                         | 0.267                      |
| Quindaro            | 0.197                     | 0.155                  | 0.197                          | 0.155                        | 0.158                         | 0.153                      |
| E.W. Brown          | 0.133                     | 0.133                  | 0.080                          | 0.080                        | 0.129                         | 0.129                      |
| R.S. Nelson         | 0.250                     | 0.221                  | 0.085                          | 0.085                        | 0.115                         | 0.000                      |
| B. C. Cobb          | 0.069                     | 0.026                  | 0.000                          | 0.000                        | 0.066                         | 0.016                      |
| Dan E. Karn         | 0.126                     | 0.126                  | 0.064                          | 0.064                        | 0.123                         | 0.123                      |
| River Rouge         | 0.034                     | 0.034                  | 0.034                          | 0.034                        | 0.032                         | 0.032                      |
| Black Dog           | 0.057                     | 0.057                  | 0.057                          | 0.057                        | 0.000                         | 0.000                      |
| Austin Northeast    | 0.153                     | 0.153                  | 0.153                          | 0.153                        | 0.336                         | 0.336                      |
| Silver Lake         | 0.256                     | 0.256                  | 0.256                          | 0.256                        | 0.242                         | 0.242                      |
| Jack Watson         | 0.037                     | 0.000                  | 0.037                          | 0.000                        | 0.000                         | 0.000                      |
| Hawthorn            | 0.132                     | 0.132                  | 0.132                          | 0.132                        | 0.000                         | 0.000                      |
| Meramec             | 0.096                     | 0.072                  | 0.069                          | 0.069                        | 0.053                         | 0.000                      |
| Blue Valley         | 0.449                     | 0.449                  | 0.449                          | 0.449                        | 0.313                         | 0.313                      |
| James River P.S.    | 0.183                     | 0.126                  | 0.096                          | 0.096                        | 0.173                         | 0.112                      |
| Lon Wright          | 0.274                     | 0.274                  | 0.274                          | 0.274                        | 0.176                         | 0.176                      |
| North Omaha         | 0.100                     | 0.067                  | 0.061                          | 0.061                        | 0.097                         | 0.050                      |
| S.A. Carlson        | 0.609                     | 0.609                  | 0.598                          | 0.598                        | 0.579                         | 0.579                      |
| Asheville           | 0.071                     | 0.037                  | 0.007                          | 0.007                        | 0.058                         | 0.025                      |
| O.H. Hutchings      | 0.318                     | 0.318                  | 0.318                          | 0.318                        | 0.154                         | 0.154                      |
| Hamilton            | 0.352                     | 0.352                  | 0.352                          | 0.352                        | 0.337                         | 0.337                      |
| Muskogee            | 0.062                     | 0.000                  | 0.021                          | 0.000                        | 0.059                         | 0.000                      |
| Northeastern        | 0.000                     | 0.000                  | 0.000                          | 0.000                        | 0.000                         | 0.000                      |
| Urquhart            | 0.015                     | 0.009                  | 0.015                          | 0.009                        | 0.000                         | 0.000                      |
| Chesterfield        | 0.056                     | 0.037                  | 0.056                          | 0.037                        | 0.039                         | 0.035                      |
| Yorktown            | 0.062                     | 0.017                  | 0.062                          | 0.017                        | 0.016                         | 0.000                      |
| South Oak Creek     | 0.132                     | 0.074                  | 0.132                          | 0.067                        | 0.000                         | 0.000                      |
| Pulliam             | 0.140                     | 0.140                  | 0.099                          | 0.099                        | 0.000                         | 0.000                      |
| Weston              | 0.019                     | 0.019                  | 0.012                          | 0.012                        | 0.007                         | 0.007                      |
disposability model differ in terms of other efficient decision making units: For the model specifications without labor, only one plant is considered efficient by both the pollution control model and the weak disposability model, but not by the traditional model. For the model specification with labor the corresponding number is zero. In total, only seven plants (13 percent of the sample) receive the same efficiency score by the pollution control model and the weak disposability model for the model specification without labor, and 10 plants (38.5 percent of the sample constrained to plants with labor data) for the model specification with labor. In the case without labor I find that 15 plants are considered more efficient by the pollution control model than by the weak disposability model, while 32 plants are considered less efficient by the pollution control model than by the weak disposability model. The corresponding numbers are 5 and 11 in the case with labor. By interpreting this result according to Fig. 1, I conclude that 32 (11) of the plants (close to 60 (42) percent of the sample) are located in an area of the weakly disposable output set where there is a negative trade-off between desirable and undesirable outputs. In other words, NOx emissions may be reduced while simultaneously increasing the electricity output—a result that is in line with the Porter hypothesis (Porter and Van Der Linde 1995), which suggests that environmental regulations may foster innovation and improve competitiveness. This hypothesis is usually rejected by economic theory and empirical assessments (Brännlund and Lundgren 2009; Palmer et al. 1995).

According to Table 2, 32 of 54 plants receive the same efficiency score by the traditional model and the pollution control model for the empirical specifications without labor, and 10 of 26 plants receive the same efficiency score by the traditional model and the pollution control model for the empirical specifications with labor. The corresponding numbers are six plants and ten plants, respectively, for the weak disposability model. Thus, the estimates of the pollution control model appear to be more similar to the traditional model than the estimates of the weak disposability model when labor is not included among inputs.

I now set out to evaluate the hypothesis that the three models’ efficiency scores are equivalent since fossil fuels and the generating capacity are unlikely to play a role in pollution control activities. To account for the possibility that labor is allocatable to pollution control I test for differences in efficiency scores for both the model specifications with and without labor. Following previous arguments I execute the tests by only considering power plants that report number of employees for the model specifications that incorporate labor.10 I apply a battery of statistical tests—the Kolomogorov-Smirnov (KSM), ANOVA, Wilcoxon rank-sum (WILC), and median (MED) tests—to evaluate the differences between the efficiency scores of the traditional production model and the two other models. The null hypotheses are that of no differences in the estimates of technical efficiency for the two “pollution control adjusted” models and the traditional production model in terms of mean and distribution. Table 3 reports the test statistics, with p values reported in brackets.

The interpretation of Table 3 is clear: there is no statistically significant difference between the efficiency scores of the pollution control model and the traditional production model, both for the empirical model specification with and without labor. The weak disposability model, on the other hand, produces efficiency scores that significantly differ from the efficiency scores of the traditional production model in the case without labor, but not in the case with labor. Overall, these results do not support the hypothesis that labor is allocatable to both pollution control and electricity generation. Pollution control for NOx emissions is capital intensive, and labor may play a small role in curbing the emissions. This may explain why my results do not indicate that labor is an allocatable input.

The differences between the efficiency scores of the weak disposability model and the traditional production

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Table 2 continued

| Plant        | Traditional Without labor | With labor | Pollution control Without labor | With labor | Weak disposable Without labor | With labor |
|--------------|---------------------------|-----------|--------------------------------|-----------|-----------------------------|-----------|
| Belle River  | 0.061                     | 0.000     | 0.061                          | 0.000     | 0.000                       | 0.000     |
| Trimble County | 0.070                   | 0.025     | 0.070                          | 0.025     | 0.011                       | 0.000     |
| A.B. Brown   | 0.053                     | 0.000     | 0.000                          | 0.000     | 0.046                       | 0.000     |
| Rodemacher   | 0.207                     | 0.207     | 0.207                          | 0.207     | 0.179                       | 0.178     |
| Southwest P.S | 0.135                   | 0.051     | 0.135                          | 0.051     | 0.105                       | 0.043     |
| Rawhide      | 0.073                     | 0.021     | 0.073                          | 0.021     | 0.060                       | 0.008     |
| Neil Simpson 2 | 0.144                  | 0.144     | 0.144                          | 0.144     | 0.000                       | 0.000     |

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10 For comparison, I also execute the tests for all 54 power plants for the model specifications with labor. In this case, no test rejects the null hypotheses for the pollution control model, but the KSM, WILC and MED tests reject the null hypotheses at the 10 percent level for the weak disposability model.
model are usually attributed to resources which are employed to pollution control, and which leads to measurement errors for the traditional measure of technical efficiency. My results illustrate that using the weak disposability model to “give weight” to emission reductions in performance measurement may not be appropriate in all settings, because differences between the weak disposability model and the traditional model are not always attributable to pollution control efforts. More specifically, I find that by including labor the efficiency scores of the weak disposability model and the traditional model become more similar—a result which is just the opposite of what was expected. I conclude that studies which use the weak disposability model to “give weight” to emission reductions should allocate more resources to identifying suitable case studies and inputs. In accordance with Sect. 2, the weak disposability approach appears to be applicable to industries that reduce emissions by pollution control in cases where some inputs are allocatable to pollution control and the intended production.

6 Summary and conclusions

This study has considered the impact of pollution control activities on the measurement of technical efficiency. The common assumption in the literature on polluting technologies, that technical efficiency estimates for environmentally regulated producers are biased because of inputs employed to pollution control activities, is critically examined. I point out that many empirical studies that rely on this assumption do not allocate resources to establishing whether it actually is a suitable assumption for the cases at hand. I use an empirical example from the U.S. electricity sector to illustrate my main point: In line with the literature on polluting inputs I consider fossil fuels, labor, and generating capacity as inputs, where only labor may possibly be considered allocatable to pollution control activities. Hence, there are no reasons to expect the traditional production model to provide biased efficiency estimates due to pollution control activities, in particular when labor is excluded from the analysis. I evaluate this proposition empirically by comparing the efficiency scores of the traditional production model to the model of Färe et al. (1989, 2005) that aims to reward producers for cleaning up pollutants. I further introduce a new approach to modeling polluting technologies that makes production possibilities dependent on the producers’ pollution control efforts. A major difference between my model and the model of Färe et al. (1989, 2005) is that pollution control efforts are considered explicitly, rather than implicitly. I use DEA to calculate efficiency scores for the three models and use a battery of statistical tests to determine whether the two models that account for pollution control efforts differ from the traditional model. I find that the efficiency scores of the traditional model and my model are not statistically different, both when labor is and is not included among inputs. However, the efficiency scores of the traditional model and Färe et al.’s model appear to be different for the empirical specification that omits labor. This difference cannot be explained by reallocation of resources to pollution control, simply because the inputs do not appear to play a role in pollution control. My results raise a question about how applicable the established models in the literature on polluting technologies are to all case studies involving polluting production. Today, the idea seems to be that “one size fits them all” as far as model applicability goes. The employment of Färe et al.’s (1989, 2005) model to empirical analyses in a wide range of sectors—including electricity generation (Färe et al. 2005), ceramic pavement (Reig-Martínez et al. 2001), agriculture (Färe et al. 2006), pulp-and-paper (Brännlund et al. 1995), and aquaculture (Liu and Sumaila 2010)—illuminates this point. My results suggest that future research on polluting technologies should question whether this practice is acceptable. The emphasis should be on identifying cases where the established production models are suitable and to identify appropriate empirical specifications, e.g. by securing that inputs which are allocatable to pollution control are included in the model.

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