Title
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ECO- VS. PRODUCTIVE EFFICIENCY:

A NEW APPROACH TO EFFECTIVE AND COMPARATIVE PERFORMANCE ANALYSIS

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ABSTRACT

Increasing social concerns over the environmental externalities associated with business activities are pushing firms to identify activities that create economic value with less environmental impact and to become more eco-efficient. However, this task has proven challenging because there is no systematic methodology to integrate undesirable outputs, such as emissions, in the calculation of economic or productive efficiency. In this paper, we develop a methodology based on the nonparametric frontier approach to measure corporate eco-efficiency, and to compare it to productive efficiency. Our eco-efficiency model rectifies several problems encountered in existing approaches. Our methodology allows us to calculate, for each firm, the reduction in emissions necessary to attain eco-efficiency. In addition, our methodology measures changes in efficiency attributed to undesirable outputs. We apply our methodology to data from 84 U.S. electric utilities in 2007. Our analysis demonstrates how incorporating undesirable outputs in the measurement of efficiency can impact the distance of the firm to the best industry practice. We describe future research directions and potential applications of the methodology for managers and policymakers.

Subject classifications: Organizational studies: Productivity; Natural resources: Energy; Programming: Linear applications.

Introduction

Increasing social concerns over the environmental externalities of business activities are pushing managers to devise strategies to mitigate environmental impact (Rugman and Verbeke 1998; Porter and Reinhardt 2007). Common examples of these strategies include pollution prevention, waste reduction, recycling, closed-loop supply chain management, and environmental management systems (Klassen and McLaughlin 1996; Corbett and Kleindorfer 2001; King and Lenox 2002; King et al. 2005; Corbett and Klassen 2006; Delmas and Toffel 2008). In all cases, managers are faced with the fundamental question of the impact of these strategies on their corporate efficiency (Ullmann 1985; King and Lenox 2001, 2002; Klassen and Whybark 1999; Klassen and Vachon 2003). When deciding to allocate resources to reduce their environmental impact, managers need to assess how these strategies will improve or decrease their corporate efficiency. However, this task has proven challenging. While there are established methodologies to measure productive efficiency, the development of methodologies to incorporate environmental performance in the measure of efficiency is more recent and still faces significant methodological challenges. In this paper, we develop a methodology to measure corporate eco-efficiency and to compare it to productive efficiency.

Eco-efficiency is generally understood as “creating more value with less environmental impact” (Huppes and Ishikawa 2005). The concept of eco-efficiency can be contrasted with the narrower view of productive efficiency, which focuses on the relationship between production inputs and outputs and ignores environmental side-effects. If the production process does not create negative externalities, these two efficiency measures should coincide.

While frontier methodologies have been extensively used for the measurement of productive efficiency for several decades (Charnes et al. 1978; Kuosmanen and Kortelainen 2005; Färe et al. 1989, 2005), the development of approaches for the measurement of eco-efficiency is more recent (Zhou et al. 2008). Frontier methodologies provide a composite efficiency score that represents the observed unit’s performance regarding multiple inputs and outputs. Given a certain level of inputs, firms on the efficiency frontier are those that produce a maximum level of outputs.

An important challenge with the measurement of eco-efficiency is to integrate into the model "undesirable" outputs such as pollution. While several models have attempted to address this issue (e.g., Hailu and Veeman 2001; Färe et al. 1989, 2005; Seiford and Zhu 2002), our analysis indicates that these models might be unreliable. Our results show that these models are insensitive to either increase or decrease in undesirable outputs. This is an important weakness because managers cannot assess how changes in undesirable outputs will impact their overall efficiency. We also find that some models could produce irregular evaluation results. That is to say, a firm's eco-efficiency may improve with an increase in its emissions. We call this situation "irregular" because undesirable outputs by definition should present a potential cost to the producing firm and the ecological system. This is especially true for emissions that are regulated. As such, a higher level of undesirable outputs should not ameliorate the eco-efficiency of a firm.

In this paper, we build on the nonparametric frontier approach to develop an eco-efficiency comparative methodology. Our methodology makes important contributions to the eco-efficiency literature by providing a solution to the problems mentioned above. In addition, our methodology allows the systematic comparison of eco- and productive efficiency scores. Existing frontier methodologies do not allow the measurement of the marginal effect of the inclusion of new variables on the firm efficiency. This limitation hampers us from measuring the impact of undesirable outputs on productive efficiency. This is an important downside since even firms in the same industry could vary dramatically in their environmental performance. Freudenburg (2005) provides evidence of the disproportion of emissions at the macro and industrial level. Using the toxic release inventory data in the United States, he finds that around 80% of the toxic release is usually produced by only 20% of the firms in an economy or sector.[1] Our methodology can help asses the effect of potential environmental policies on each firm's relative efficiency within a specific sector.

In view of the usefulness of comparing the eco- and productive efficiency, our methodology holds great potentials for eco-efficiency analysis in other fields such as business strategy, finance, and public policy. Understanding the difference between eco- and productive efficiency can allow practitioners in both the private and public sectors to tap into the eco- vs. productive efficiency framework. The difference between eco-efficiency and productive efficiency scores reflects a firm's relative efficiency gain or loss exclusively due to its environmental impact. Managers can benefit from knowing how the undesirable outputs of their firms can influence their relative efficiency compared to their competitors. Such information can be helpful to managers when allocating resources to mitigate environmental impact. Policymakers can also use this information in policy design and decision-making. We will elaborate on these applications later in this paper.

We illustrate the advantages of our methodology by applying it to data from 84 U.S. investor-owned electric utilities in 2007. The electricity sector has been one of the major contributors of greenhouse gases, and has been under stringent scrutiny for its environmental performance (Majumdar and Marcus 2001; Fabrizio et al. 2007; Delmas et al. 2007). Our methodology allows us to calculate, for each firm, the reduction in emissions necessary to reach the eco-efficiency frontier. Specifically, the median firm in the sample in regards to eco-efficiency scores would need to reduce its total SO_2, NO_x, and CO_2 emissions by 50.0%, 51.2%, and 32.9%, respectively to reach the eco-efficiency frontier. Our findings also show a positive correlation between eco and productive efficiency, indicating that productive efficient firms also tend to be eco-efficient as well. Finally, our results indicate that around 23% of the electric utilities in our sample became more inefficient when incorporating environmental performance in the efficiency evaluation. This is consistent with the findings of Freudenburg (2005) and supports the idea that pollution might be disproportionally related to sales or production for a minority of firms.

In the next section we introduce the nonparametric frontier methodology. This is followed by a discussion of four representative efficiency models that have been developed to incorporate undesirable outputs and of their limitations to measure eco-efficiency. In Section 3 we introduce our eco-efficiency model, and demonstrate its advantages. In Section 4, we present our comparative methodology to contrast eco-efficiency to productive efficiency. In Section 5 we apply our model to the U.S. electric utility sector. In the final section we summarize our findings and discuss how the model can be used in various contexts.

Frontier methodology and existing models

We begin this section by introducing the nonparametric efficiency model. Next we review four efficiency models that have been developed to deal with undesirable outputs. Using the U.S. electric utility data, we illustrate the problems of these four existing approaches.

1.1 Fundamental concepts of frontier methodologies

The nonparametric frontier methodology has been extensively used in the operation literature to evaluate firms according to their multiple inputs and outputs (Charnes et al. 1978; Banker et al. 1984). The frontier methodology uses linear programming to convert multiple inputs and outputs of firms into a single measure of relative efficiency. A piecewise linear industry best practice frontier is constructed using the observations in the sample. The set of feasible production plans, or technology set, are the input-output combinations enveloped by the frontier. If the firm is on this frontier, it is considered efficient. If it is not on the frontier, its radial distance from the best practice frontier is a measure of the firm's inefficiency.

1.2 Formulation of technology sets

In the frontier methodology, the set of feasible production plans or technology set can be formulated as follows (Charnes et al. 1978):

$$
\begin{aligned}
\Omega := \{(X,D) &: X \text{ can produce D}\} \\
= \{(X,D) &: \sum_{k=1}^{K} z_k x_{km} \le x_m, \text{ for } m = 1,..,M && \text{(1-1)} \\
&\sum_{k=1}^{K} z_k d_{kn} \ge d_n, \text{ for } n = 1,..,N && \text{(1-2)} \\
&z_k \ge 0, \quad \text{for } k = 1,...,K \ \} && \text{(1-3)}
\end{aligned}
$$

where K is the number of firms in our sample, $(x_{k1},...,x_{kM})$ and $(d_{k1},...,d_{kN})$ are the observed input and output vectors of firm i, and the technology set is the collection of all feasible $(X,D)=(x_1,...,x_{m,}d_1,...,d_n)$. The efficiency of a firm can then be computed as an optimization problem, in which we measure the distance between the firm and the efficiency frontier. Note that all production outputs in model (1) are desirable. This means that their value is non-decreasing with increase in quantity. In reality, however, producing desirable outputs can create undesirable by-products as well, such as waste and air emissions, which will impose burdens on the environment. Therefore, to comprehensively assess firm efficiency, we need to incorporate undesirable outputs in the formulation. In the next section we study the efficiency models for production processes that generate both desirable and undesirable outputs.

1.3 Current efficiency models for undesirable outputs

The primary distinction between the traditional production model and the one with undesirable outputs is that, in addition to maximizing their desirable outputs, efficient firms should also minimize their undesirable outputs. Thus we need to differentiate these two types of outputs both in the production model (e.g., model (1)), and the efficiency measure (i.e., the way we measure the distance between the evaluated firm and the efficiency frontier). One approach is to treat undesirable outputs as inputs to be minimized in the efficiency model (Berg et al. 1992). We refer to this approach as the UINP model (i.e., undesirable outputs treated as inputs). Some other studies distinguish undesirable outputs by imposing a weak disposability assumption on them. This assumption means that, for any input-output combination in the technology set, a decrease in undesirable outputs must be accompanied by a decrease in desirable outputs. Examples of such models include the directional distance function (DDF) (Chambers et al. 1998) and the hyperbolic efficiency model (Färe et al. 1989). These two models also alter the traditional efficiency measure by requiring that undesirable outputs be reduced when outputs increase.[2] Another stream of research takes a more heuristic approach to undesirable outputs. Seiford and Zhu (2002) substitute undesirable output variables in the efficiency modes by auxiliary output variables. These new variables are computed by adding a positive scalar to the original undesirable outputs after multiplying them by minus one. Thus maximizing these new output variables is equivalent to reducing the underlying undesirable outputs.

In this paper we will focus on the four following representative approaches to measuring efficiency in the presence of undesirable outputs: the UINP model, the hyperbolic efficiency model, the directional distance function (DDF model), and Seiford and Zhu's model (SZ model). More detailed descriptions of these models and their formulations are provided in Appendix A. We summarize modeling assumptions and ranges of efficiency scores of these four models in Table 1. Note that in all four models, the efficiency status is achieved when a firm obtains the lower-bound value (i.e., one or zero), which means that further expansion of desirable outputs and reduction of undesirable outputs is impossible.

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[Insert Table 1. about here]

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In the next section, we use data on electricity production to test these four models.[3] We illustrate that these efficiency models not only fail to capture actual fluctuations in undesirable outputs, but also tend to produce misleading efficiency measurement results.

1.4 Illustrative examples: Assessing the eco-efficiency of electric utilities

We use data on utilities' characteristics and environmental performance from the U.S. Federal Energy Regulatory Commission (FERC) Form Number 1 (U.S. DOE, FERC Form 1), from the U.S. Energy Information Administration (Forms EIA-860, EIA-861, and EIA-906), and from the U.S. Environmental Protection Agency Clean Air Market Program's website. After merging these related databases, we retain 84 major investor-owned electric utilities representing 59% of the total U.S. electricity production by utilities. We focus on large investor-owned firms because these companies represent the majority of the industry electricity and its pollution generation. These are the biggest and most visible electric utilities. The results of our analysis should be extrapolated to smaller firms with a degree of caution.

The descriptive statistics of the variables considered are reported in Table 2. We consider four input variables (plant value, total operation & maintenance expenditure, labor cost, and electricity purchased from other firms). We consider one desirable output (total sales in MWH) and three undesirable outputs. The undesirable outputs are sulfur dioxide (SO_2), nitrogen oxide (NO_x), and carbon dioxide (CO_2), of which SO_2 and NO_x are regulated by the U.S. Environmental Protection Agency (EPA) under the Acid Rain Program.[4]

The choice of input and desirable output variables follows previous productive efficiency calculations in the electricity sector (e.g., Majumdar and Marcus 2001; Delmas and Tokat 2005; Delmas et al. 2007).

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[Insert Table 2. about here]

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Based on the electric utility data, we construct three scenarios to test the four models covered in the previous section. Our purpose is to verify how sensitive the models are in detecting increases in undesirable outputs. In the first scenario, we use the original input output data. In the second scenario we double one undesirable output (SO_2) for *the evaluated firm*, while the data for all the other firms remain unchanged. In the third scenario we double all undesirable outputs for the evaluated firm. So for example, when firm *a* is evaluated in the second scenario, we will double SO_2 u_{a1} to be $2u_{a1}$, without changing the data for all the other firms; in the third scenario we double all firm *a*'s undesirable outputs (SO_2, NO_x, and CO_2) to be $2u_{ap}$ for $p = 1,...,P$. Intuitively we are expecting that firms' efficiency does not increase when emissions increase. That is, firms should become more inefficient when their emissions are doubled, which represents a massive surge in emissions. So if in the course of our experiment, we find problems in these models, then further experimentation with greater increases can be safely omitted.

The experimental results can be found in Table 3. Following Färe et al. (2005), we designate the directional vector (g^d, g^u) in the DDF model as $(1,1)$ and, for ease of comparison, we add 1 to the obtained DDF score. In this table we present the efficiency scores obtained from the three existing models introduced earlier. The last three columns of the table report efficiency scores from our eco-efficiency model, which will be introduced in the next section. The efficiency scores are equal to or larger than 1. A score of 1 means that the firm is on the efficiency frontier. Higher scores indicate higher *inefficiency* and mean that the firm is more distant from the efficiency frontier.

The results indicate two main problems in the existing approaches: insensitivity to changes in undesirable outputs, and irregular results where firms become more efficient when they produce more undesirable outputs. All four models examined in this paper show insensitivity to changes in outputs. For the UINP model, we find that some firms maintain their efficiency score under different scenarios (e.g., firms 2, 6, and 15 in columns 1 to 3). For efficient firms (e.g., firm 2), this may be understandable, because these firms can still outperform other firms after their emissions are doubled in scenarios 2 and 3. For inefficient firms (e.g., firms 6 and 15), however, this is not reasonable, since increases in emissions should move them further away from the efficiency frontier, and thus increase their relative *in*efficiency. The SZ model exhibits a more serious insensitivity problem (columns 10 to 12). For almost all firms, the efficiency scores from the SZ model increase less than 1% in comparison to their baseline scores. In addition, more than 50% of the firms receive the same efficiency scores in these two scenarios. Finally, for the hyperbolic and DDF models (columns 4 to 6, and 7 to 9), we see a considerable increase in the number of efficient firms in all three scenarios (average 75% and 72% in the hyperbolic and DDF models, as compared to the 37% and 20% in the UINP and SZ models), which indicates that firms can attain efficient status more easily in these two models.

The hyperbolic and DDF models also suffer from irregular results. For example, firms 1 and 13 become more efficient with increases in undesirable outputs. This is contrary to the general intuition that firms would *not* become more efficient when they increase their undesirable production. Therefore these two models are not very reliable under either proportional or non-proportional increases in undesirable outputs. These insensitivity and irregularity issues still exist when we reverse the above experiments to reduce the emissions of the evaluated unit. These results provide important insights: these four models do not reflect increases in undesirable outputs, and they also generate counter-intuitive results.

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[Insert Table 3. about here]

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MATHEMATICAL FORMULATIONS

We have shown evidence that existing approaches are insensitive to increase in undesirable outputs. We can attribute these problems to two characteristics of the conventional efficiency measure. In the ratio measure, efficiency scores in general represent a proportional change of the input or output vector. Similarly, DDF maps the evaluated unit to the frontier following a pre-determined directional vector. This design greatly restricts the ability to measure changes in environmental outputs. In this section we will propose a model that can not only overcome these problems, but also provide a comprehensive measurement of eco-efficiency. In our eco-efficiency model, we inherit the nonparametric frontier model with undesirable outputs, but we propose a new efficiency measure that allows inefficient firms to reach the efficiency frontier without requiring them to follow a pre-determined direction for improvement.

1.5 Eco-Efficiency model

Our eco-efficiency model is presented below:

$$E(x,d,u) := \max \frac{1}{N+P}\left(\sum_{n=1}^{N} \tilde{g}_n^d \big/ d_{1n} + \sum_{p=1}^{P} \tilde{g}_p^u \big/ u_{1p}\right) \quad (2\text{-}1)$$

$$\text{s.t.} \quad \sum_{k=1}^{K} z_k x_{km} \le x_{1m}, m = 1,...,M \quad (2\text{-}2)$$

$$\sum_{k=1}^{K} z_k d_{kn} \ge d_{1n} + \tilde{g}_n^d, n = 1,...,N \quad (2\text{-}3)$$

$$\sum_{k=1}^{K} z_k u_{kp} = u_{1p} - \tilde{g}_p^u, p = 1,...,P \quad (2\text{-}4)$$

$$z_k \ge 0, \tilde{g}_n^d \ge 0, \tilde{g}_p^u \ge 0, \quad \text{for all } k, n, \text{ and } p \quad (2\text{-}5)$$

Unlike in the radial traditional efficiency measure, we relax the assumption that the evaluated firm should reach the efficiency frontier by proportionally changing its undesirable and desirable outputs (cf. the objective functions of models (5) to (8) presented in Appendix A). This is because in practice, there is no guarantee that firms would always improve their efficiency following this proportional path. Thus it would be unrealistic to measure their efficiency as such. Another benefit of this formulation is that the benchmark target for each firm must be efficient, while the radial efficiency measure could identify dominated points as benchmark targets. We will illustrate this issue shortly in this section. Lastly, we choose to maximize the objective function in order to assure that the evaluated firm is benchmarked with an efficient firm on the frontier. The variables $\tilde{g}_n^d$ and $\tilde{g}_p^u$ in model (2-1) represent the amount of output improvements that the evaluated firm can make to reach its benchmark target on the efficiency frontier. Correspondingly, the objective function is the average magnitude of these improvements.

The objective value of equation (2-1) represents the overall degree of output efficiency. It is calculated as the average amount of potential output improvement divided by the observed output value, d_{1n} and u_{1p} in equation (2-1). The index value ranges from zero to infinity: zero value means that the evaluated firm is on the efficiency frontier and has no slack values (hence the firm is *efficient*). On the other hand, when a firm has non-zero value, the larger the value, the more inefficient the firm is. The constraints of this problem are similar to those of the DDF model presented in Appendix A. Therefore we also assume that undesirable outputs are weakly disposable, namely the reduction of undesirable outputs is not free, and will entail some loss of desirable outputs.

The eco-efficiency score provides an aggregate measure of a firm's relative efficiency compared to other firms in the sample. After solving the eco-efficiency model, however, we can also identify the efficiency target that the evaluated firm can emulate. Specifically, the benchmark target for firm *k* can be obtained as:

$$(x_{km}, d_{kn} + \tilde{g}_n^{d*}, u_{kp} - \tilde{g}_p^{u*}) \text{ for all } m, n \text{ and } p \qquad (3),$$

where $(z_k^*, \tilde{g}_n^{d*}, \tilde{g}_p^{u*})$ is the optimal solution to model (2).

1.6 Properties of the eco-measure

Before we apply the eco-efficiency model to the electric utility data for a comparison, we will show some important properties of the model. Proofs of these results are provided in Appendix C.

Theorem 1 shows that our eco-efficiency model is unit-invariant in inputs and all outputs:

Theorem 1. $E(x_{km}, d_{kn}, u_{kp})$ **is homogeneous of degree zero in** x_{km}**,** d_{kn}**, and** u_{kp}**; i.e., if we replace the original data** (x_{km}, d_{kn}, u_{kp}) **by** $(\alpha x_{km}, \beta d_{kn}, \gamma u_{kp})$ **for all *k*, where** $\alpha, \beta,$ **and** γ **are arbitrary positive numbers, we still have** $E(\alpha x_{km}, \beta d_{kn}, \gamma u_{kp}) = E(x_{km}, d_{kn}, u_{kp})$ **for all *k*.**

We already witnessed the detrimental effect of unit dependence in our illustration of the DDF model (see Table 3). Without the homogeneous property, the efficiency output would depend on the unit of measurement (e.g., in pounds, kg, or tons; or in Euros or dollars).

Another important property that needs to be carefully verified is the quality of the eco-efficiency measure. Ideally, we would expect that eco-efficient firms, as identified by the model, should be "at least as good as" any members in the technology set. Conversely, firms will be regarded as inefficient only when they have an eco-performance inferior to any feasible units in the technology set. To answer this question, we need to first define the dominance relationship in the technology set.

Definition 1 (Domination relationship). The production plan $(x_{km}, d_{kn}, u_{kp}) \in \Omega$ **is non-dominated if there does not exist any** $(x_{km}, d'_{kn}, u'_{kp}) \in \Omega$ **such that** $(x_{km}, d'_{kn}, u'_{kp}) \neq (x_{km}, d_{kn}, u_{kp})$ **while** $d'_{km} \geq d_{km}$ **and** $u'_{kp} \leq u_{kp}$. **Otherwise** (x_{km}, d_{kn}, u_{kp}) **is dominated.**

The next theorem shows that the eco-efficiency status is equivalent to the non-dominance status in the technology set.

Theorem 2. $E(x_{km}, d_{kn}, u_{kp}) = 0$ **if and only if** (x_{km}, d_{kn}, u_{kp}) **is non-dominated in** Ω **.**

The development of our efficiency index is illustrated in Figure 1. The first term in the objective function is the ratio between potential desirable output increases and the current output value. In Figure 1, the first term of firm *e* is measured by *dd** (potential improvement) divided by *0d* (current output). For the undesirable output, the related efficiency is similarly calculated as *uu** divided by *0u*. Our eco-efficiency measure has one important merit over the radial measure, namely, it can account for input and output slacks in the evaluation (Tone 2001). For example, if we observe four production units *a, b, c, e*, and *f* as shown in Figure 1, using the conventional efficiency measure we would identify *f'* as its benchmark target by simultaneously contracting the undesirable output (going toward the left) and increasing the desirable output (going upward). The evaluation score would therefore be determined based on *f'*. We can, however, observe that *f'* is actually dominated by point *c*, which produces the same amount of desirable outputs as *f'* but less undesirable outputs. Our approach can help the inefficient unit, such as *f*, indentify a non-dominated target, and therefore provides an accurate assessment of the productive efficiency.

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[Insert Figure 1. about here]

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1.7 Illustrative results and comparisons

We apply our model to the electric utility data described in the previous section. The efficiency results are reported in Table 3 (column 13 to 15). Compared to previous models, our eco-efficiency model has a greater ability to detect non-proportional increases in undesirable outputs. Specifically, eco-efficiency scores are monotonically increasing in scenarios 2 and 3.

For example, firm 1 in the UINP model obtains the same efficiency score in both scenarios 1 and 2. In the SZ model, firm 1's score is consistently 1.28. In the case of the hyperbolic and DDF models, firm 1 is inefficient in the baseline scenario but becomes efficient in the second scenario, while in the third scenario it becomes inefficient again. By contrast, firm 1's eco-efficiency score is increasing in these three scenarios: it increases from 1.37 to 1.62, then to 2.12, which is in line with our intuition that "more emissions mean more inefficiency."

In conclusion, we developed a general model to assess firm performance considering multiple inputs, and desirable and undesirable outputs. We showed through an illustrative example that our eco-efficiency model can address the challenges identified in the previous models. In addition, the model is unit-invariant and is guaranteed to identify non-dominated benchmark targets on the efficiency frontier. In the next section, we develop a systematic methodology to compare eco-efficiency to productive efficiency.

MARGINAL EFFECT OF UNDESIRABLE OUTPUTS: QUANTIFYING THE ECO- VS. PRODUCTIVE EFFICIENCY DIFFERENCE

For managers and policymakers, however, it is important to realize the impact of environmental factors on their corporate performance. For example, policymakers might want to compare productive efficiency to eco-efficiency to help them assess the impact of new regulations. Firms that receive the strongest shocks; i.e., those that have significant gaps between the evaluations *with* and *without* undesirable outputs, might be those that will be most impacted by, for example, increases in regulation stringency. This type of information will be extremely helpful in ensuring the impact of future regulations on firms' efficiency (Kirkpatrick and Parker 2004). This information is also a valuable input to the strategic environmental assessment (SEA) or environmental impact assessment of corporate activities, which are mandatory reports in many countries (see, e.g., Schmidt et al. 2005).

Intuitively these tasks can be carried out by comparing the outputs from two models, one considering all variables (X,D,U) and the other considering only a subset of variables (X,D). However, this methodology can be biased. Specifically, adding new variables to an efficiency model will introduce a mixed impact on the result: first there is an effect related to the introduction of new variables (i.e., the model grows in size), and second there is an effect from the variables themselves (Pastor et al. 2002). The efficiency score, however, is a result of both types of effect. In practice, it is difficult, if not impossible, to disentangle these two effects in the efficiency score. Therefore we need to remove the influence on efficiency scores due to the inclusion of new variables, so we can isolate and estimate the second type of effect, the one due to variations in the undesirable production among firms.

For the first type of effect, it is well known that, when the number of variables increases, firms tend to obtain higher efficiency in the nonparametric efficiency model (Dyson et al. 2001). Firms measured by the existing efficiency models presented in Appendix A will all appear to be equally or more efficient after we include undesirable outputs. This is because adding one additional output variable is equivalent to imposing one more constraint to these models. This also means that, no matter how "dirty" the firm might be, inclusion of undesirable outputs always increases efficiency. It follows that comparing eco-efficiency to productive efficiency will make no practical sense, and therefore this simple methodology should be abandoned. By contrast, our model by construction does not have the above problem, because the environmental performance is explicitly accounted for in the objective function. Therefore inclusion of undesirable variables can lead to either increased, decreased, or unchanged scores, depending on the firm's relative environmental performance. However, the change in eco-efficiency scores is due to the combined effect of introducing new variables and the within-variable variation, as described above. Next we propose a methodology to extract the second type of effect from the eco-efficiency score.

1.8 Developing a comparative framework

In our comparative approach we build a productive efficiency model that can be compared to the eco-efficiency model. Our productive efficiency model has a similar formulation to the eco-efficiency model and considers all production variables (X, D, U), except that we replace all observations of undesirable outputs with a positive constant. Formally, we replace all undesirable outputs $U_{kp} = (u_{k1}, \ldots, u_{kP})$, $k = 1, \ldots, K$ in our data, by an arbitrary constant $\mu > 0$. Since our efficiency model is unit-invariant, this constant can be arbitrarily chosen. By doing so, the model can reflect firms' difference in productive efficiency independently from their environmental performance (i.e., firms all have equal environmental performance). However, the productive efficiency model is of the same size as the eco-efficiency model. Scores obtained from this model have therefore been adjusted for the inclusion of undesirable outputs, and are readily comparable to the eco-efficiency scores. By comparing the productive and the eco-efficiency scores, we can estimate the pure environmental performance, as well as the impact of introducing environmental indicators on firms' relative efficiency. As a final point, we should note that our methodology—replacing undesirable outputs with constants—is inapplicable to those existing efficiency models in Section 2.[5]

Having developed the productive efficiency model, we proceed to define a simple index to quantify efficiency changes when we switch from the productive to the eco-efficiency model. Denote the efficiency score for firm j from the productive efficiency model as TE_j. Then we define a simple index to measure the impact of including environmental factors on firm j:

$$(1 + TE_j) \big/ (1 + E_j), \quad (4)$$

where we add one to both eco- and productive scores because the eco-efficiency score can be zero. Through this index we want to measure the changes in efficiency scores, which can be interpreted as the productivity consequences associated with undesirable outputs. When the index is equal to one, it means that the firm's efficiency is not affected by the environmental factors. An index value higher than one implies that this firm appears to be more efficient in the eco-efficiency model, so the firm would benefit from incorporating undesirable outputs into the evaluation process. Conversely a value less than one means that this firm is subject to a negative impact on its relative efficiency, once environmental criteria are included.

EMPIRICAL ILLUSTRATIONS

In this section we illustrate our comparative approach by applying it to the data from 84 U.S. electric utilities in 2007, which was also used in Section 2.

1.9 Results and interpretations

We plot the eco and productive efficiency scores of all sampled firms in Figure 2A and 2B.[6] Recall that efficiency scores are an aggregate measure of the relative efficiency of firms. Scores in these two models can range from zero to infinity. A zero score signifies that the firm is on the efficiency frontier. Non-zero values indicate the average amount of possible output improvement per output (i.e., expand desirable and reduce undesirable outputs), standardized by the evaluated firm's output quantities. The actual improvement target for each firm can be computed using the optimal solution to the eco-efficiency model, which was mentioned in Section 3. For example, firm A in Figure 2A has an eco-efficiency score of 0.70. This means that firm A can improve its total sales and reduce three types of gas emissions by an average of 0.70 standardized units per output to reach the efficiency frontier. We know that in our sample, firms emit on average 80,854 tons of SO_2, 28,450 tons of NO_x, and 19,650,461 tons of CO_2. Firm A emits 308,149 tons of SO_2, 79,591 tons of NO_x, and 59,053,986 tons of CO_2. Using Equation (3), we can calculate the amount of reduction in emissions for firm A after we solve the eco-efficiency model (2). The results indicate that firm A should reduce 302 thousand tons of SO_2, 727 thousand tons of NO_x, and 53,530 tons of CO_2 emissions to become eco-efficient.

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[Insert Figure 2A and 2B. about here]

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We take the example of three electric utilities to illustrate our methodology. From Figure 2A, Firm A has the highest eco-efficiency score of 0.70, which is twice the mean of the eco-efficiency scores in the sample (~0.2873). By comparison, Firms B and C are both eco-efficient with a score of 0. Turning to Figure 2B, however, we can see that both Firm A and Firm C attain productive efficiency with a score of zero, while Firm B is productive inefficient (~0.89). Thus firms that obtain eco-efficiency are not necessarily productive efficient as well, and vice versa.

To understand the relationship between a firm's eco- and productive efficiency scores, we can look at the ratio of the two scores. Figure 3 presents the ratio of productive efficiency divided by eco-efficiency. This ratio indicates how a firm's relative efficiency is affected when undesirable outputs are considered. Firm A in the figure has a low ratio (~0.59), indicating that its relative efficiency deteriorates by 41% after switching to the eco-efficiency model. Firms A performs better in the productive efficiency model than in the eco-efficiency model. Firm A's poor eco-efficiency score (0.70) can largely be attributed to its low environmental performance. Despite its inefficient status in the productive efficiency model, Firm B has a ratio larger than one (~1.83). This indicates that the primary source for Firm B to achieve eco-efficiency is its superior environmental performance. Firm C obtains a ratio of 1 because its efficiency scores are consistent in two models.

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[Insert Figure 3. about here]

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The descriptive statistics of the results are presented in Table 2. Among the 37 eco-efficient firms, 17 firms are productive efficient. This result suggests that productive efficient firms tend to be eco-efficient as well. However, the eco-efficiency and productive efficiency scores for the entire sample exhibit only low correlation (~0.3871) and are significantly different. The ratio of the mean of the two efficiency scores is 1.1191, which is larger than one. This means that on average firms are relatively more efficient in the eco-efficiency model than in the productive efficiency model. This indicates that on average the electric utility firms in our sample tend to be closer to the efficiency frontier when undesirable outputs are incorporated in the model.

We can classify firms into three groups according to the ratio defined in (4), and rate firms according to their relative efficiency positions in two models. The first group includes firms with a ratio larger than one (46 firms, 54.8%). This occurs when the eco-efficiency score is higher than the productive efficiency score. This means that firms in this group are more efficient when environmental outputs are incorporated. By contrast, firms with a ratio less than one (19 firms, 22.6%) become more inefficient when their environmental performance is included in the evaluation. The third group of firms has a ratio equal to one (19 firms, 22.6%). So the relative efficiency of firms in this group will not be affected by the inclusion of undesirable outputs.

These results reflect the distribution of the undesirable outputs. In table 2, we observe that the coefficients of variation of the undesirable outputs, which is calculated as the standard deviation divided by the mean, are much higher than those of the desirable output (total sales) and of all inputs. This means that the undesirable outputs in this example are relatively more dispersed in their distributions than all the other variables. Histograms of the undesirable outputs presented in Figure 4 also indicate that the distribution of undesirable outputs might be more right-skewed than the desirable output (sales).[7] In other words, a higher percentage of firms have a lower level of undesirable outputs as compared to the desirable output and few firms have very large numbers. This is consistent with the findings of Freudenberg (2005) who observed that the production of toxic releases is marked by a disproportion to economic activity and that approximately 20% of the firms produce 80% of the pollution. Our results indicate that around 23% of the electric utilities in our sample became more inefficient when incorporating environmental performance in the efficiency evaluation.

DISCUSSION AND CONCLUSION

As environmental awareness and pressure increases, there are pressing needs for managers and policymakers to use effective tools to assess firms' environmental and productive efficiency. In this paper we propose a new eco-efficiency model to overcome some of the problems identified in four commonly used frontier evaluation approaches. We show that these approaches sometimes fail to produce robust results and are fairly insensitive to increases in undesirable outputs.

This paper makes important contributions for both eco-efficiency theorists and practitioners. For the former, this paper identifies and provides effective solutions to the problems of current frontier approaches that measure environmental efficiency. In particular, we show that these approaches cannot reflect variations in the undesirable outputs, which is the most critical feature of an eco-efficiency metric. For researchers, this also means that, after two decades of development, the literature on eco-efficiency has some important limitations, whereas the demand and pressure to scrutinize firms' environmental performance continuously increase. In this paper, we develop an eco-efficiency model using the nonparametric frontier methodology. Our methodology can help to identify differences in eco-efficiency and productive efficiency scores. Using an empirical dataset, we show that our approach provides more robust measurement than the existing efficiency model. Based on our eco-efficiency model, we propose a comparative framework to analyze the impact of environmental indicators on the relative performance of firms when environmental indicators are introduced to the model. We apply the methodology to data from U.S. electric utilities. We find that productive efficient firms tend to be also eco-efficient. This implies that, in our sample, firms that have better productive performance tend to have better environmental performance. By comparing the eco- and productive efficiency scores, we can identify firms that would be most impacted by the inclusion of environmental variables. In our sample, we find that the efficiency of around 20% of the firms is negatively affected by the inclusion of environmental indicators in the evaluation. This methodology has created a new path for policymakers and managers to measure and analyze eco-efficiency. Next we provide a discussion on the academic and practical implications of our methodology. We then review the limitations of the current study and the opportunities for further research.

1.10 Potential applications of the methodology

There has been a continuous debate in the literature on whether improved environmental performance could lead to financial gains and long-term competitive advantage (Hart and Ahuja 1996; Klassen and McLaughlin 1996; King and Lenox 2001). The mixed findings from the research on corporate social performance might be ascribed to the use of different performance measures (Ullmann 1985; Griffin and Mahon 1997). Our methodology in this regard can provide a more comprehensive measurement of efficiency than those previously used.

At a more practical level, our approach could be useful not only to managers but also to other stakeholders who want to compare firms based on their environmental performance. For example, investors are increasingly using screens based on environmental and social responsibility to select or avoid investing in companies based on environmental and social preferences (Chatterji et al. 2009).[8] Chatterji and Levine (2006) note that even major Socially Responsible Investment indexes employ different evaluation metrics. This creates great difficulties in comparing firms on these dimensions. Our eco-efficiency model can address some of these challenges. It provides a generic evaluation instrument for production processes concerning multiple inputs, and desirable and undesirable outputs. The eco-efficiency model, in combination with the comparative methodology that we developed, constitutes a powerful tool that allows for a comparison of firm performance despite differing data structures. See also Chen and Delmas (2009) for an example of efficiency analysis of the corporate social performance data.

Our approach can also be used by policymakers to design new regulations or identify the effectiveness of current regulations. In our previous application to the electricity industry, we have classified firms according to their sensitivity to the addition of environmental constraints or undesirable outputs in the measure of efficiency. Policymakers can further refine the classification by setting up threshold values for efficiency. For example, it is possible to relegate firms having efficiency ratios below one standard deviation from the mean ratio (<0.93) to the outlier group.[9] These are the firms that have relatively low ratios and will be those more severely impacted by changes in regulation. In our sample, this outlier group contains 7 firms, approximately 8% of the entire sample. Similarly, we can also set the threshold by percentiles: e.g., dividing firms into four categories by quartiles. In this way we can divide the 84 firms into four groups of 19, 22, 22, and 21 firms, from the lower to the upper quartiles. This kind of information is useful for regulatory impact assessments, in which feasibility, cost, and benefit of the new regulatory design need to be comprehensively contemplated (Kirkpatrick and Parker 2004).

1.11 Limitations and future research

Our study is not without limitations. The first limitation of the current study is that electric utilities in the sample are not clustered according to their technology profile. For example, we would expect that electric utilities that operate largely based on coal generation are more likely to produce higher levels of emissions as compared to firms using more renewable resources in electricity generation. Future research could measure the relative performance of firms against a smaller group of peers classified according to their generation technologies.

In this paper we only apply our methodology to cross-sectional data. We see a promising research direction in applying the methodology to longitudinal panel data to further analyze the causal impact of environmental regulations on efficiency and how efficiency scores can help predict the development of market and non-market strategies.

The efficiency ratio defined in our methodology assesses the marginal impact of including all undesirable outputs. In practice, some pollutants may be currently unregulated but subject to future regulation. In this situation, we can also adapt our methodology to measure the marginal impact on efficiency from including one or a subset of undesirable outputs. This can be done by replacing the undesirable output variables of interest with constants.

For practical purposes, great research opportunities also exist in developing a hybrid approach combining our methodology with simulation techniques. Before investing in environmental activities and processes, it is helpful for managers to foresee the resultant efficiency ratio. To achieve this, we need to model both the uncertainty about the implementation process of the improvement activities and the potential strategic responses from competitors. By doing so, managers can perform a "what-if" analysis to estimate the outcome associated with the adaptation of different strategic options. See, for example, Chen et al. (2009) for an application of simulation with an efficiency model to operations planning. Another promising direction is to generate multiple scenarios regarding caps on emissions or other environmental variables. Policymakers may be interested to see how the caps will affect the eco-efficiency of firms (e.g., how will a specific percentage of reduction of CO_2 emissions impact efficiency). This kind of analysis can be conveniently implemented as an additional constraint on the undesirable outputs in the eco-efficiency model.

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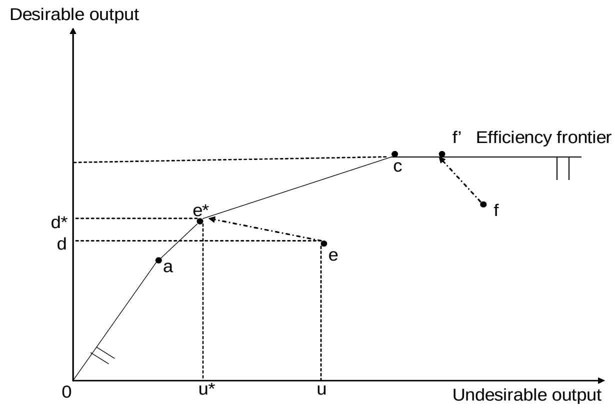
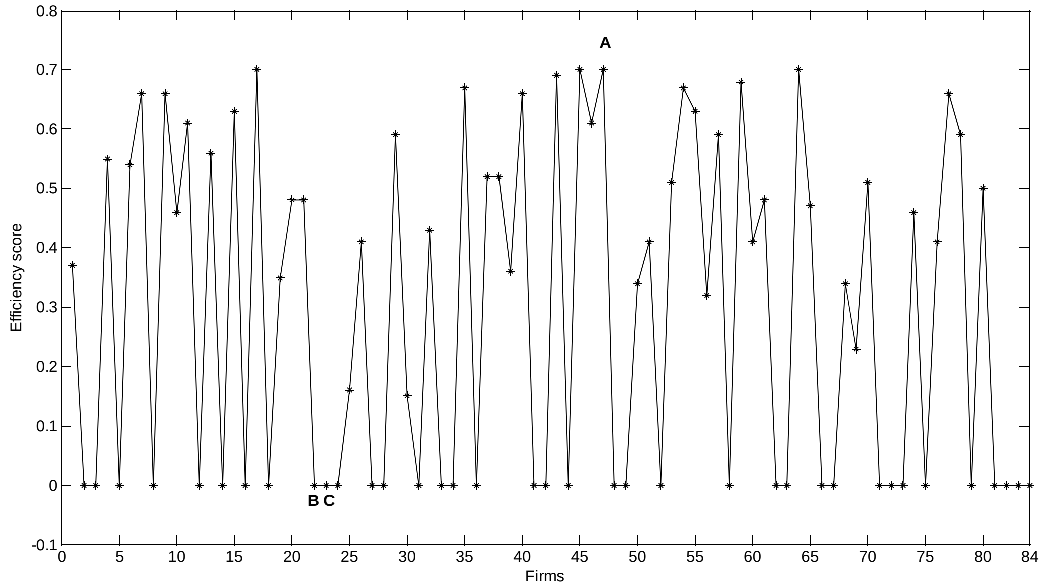


Figure 1 Illustration of the efficiency measure

A. Eco-efficiency scores



B. Productive efficiency scores

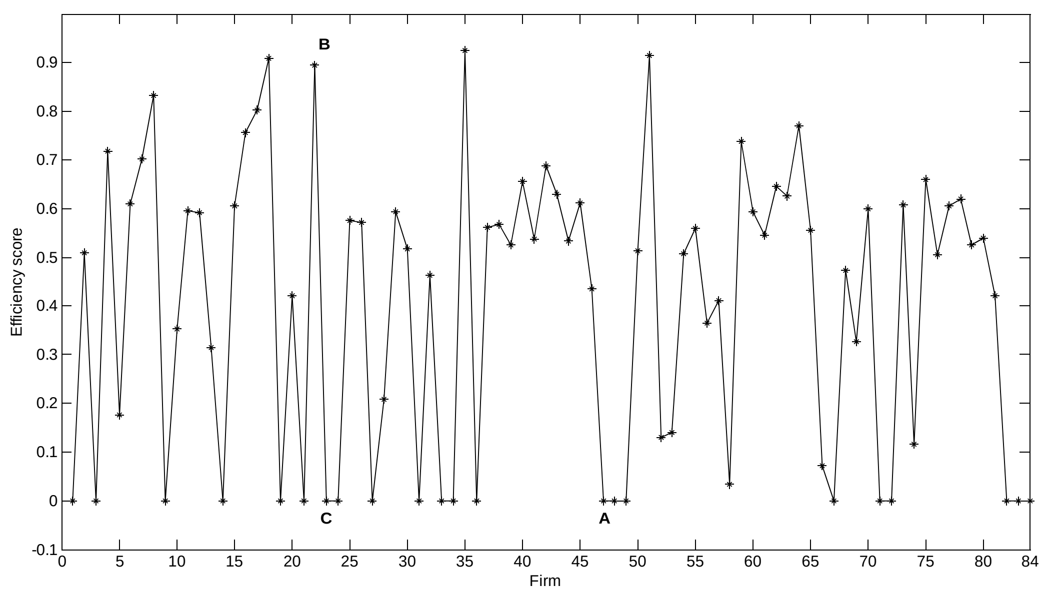


Figure 2 Scores from two efficiency models

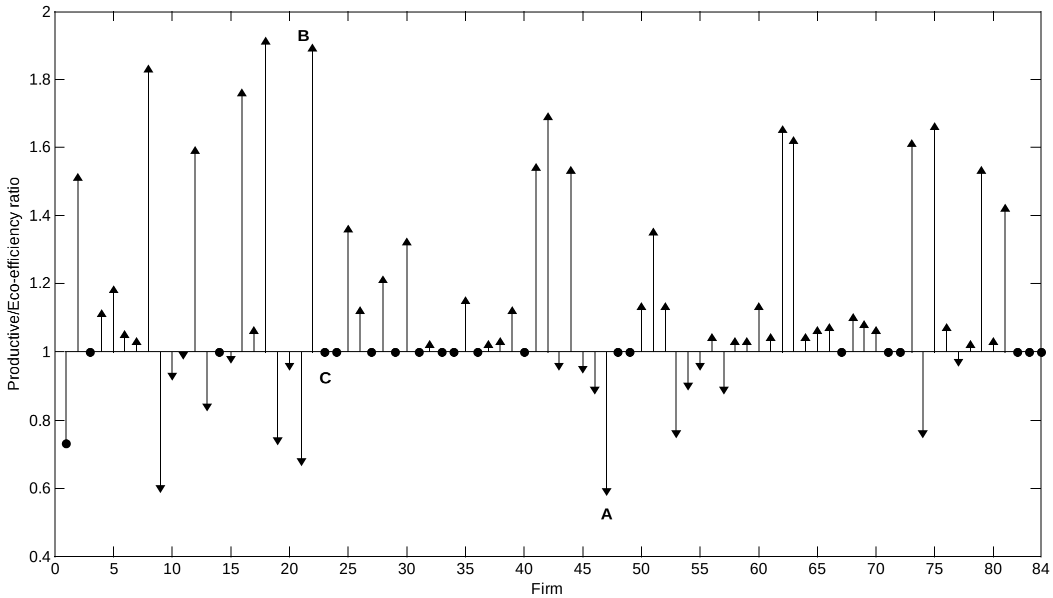


Figure 3 Ratio changes between the eco and productive efficiency models

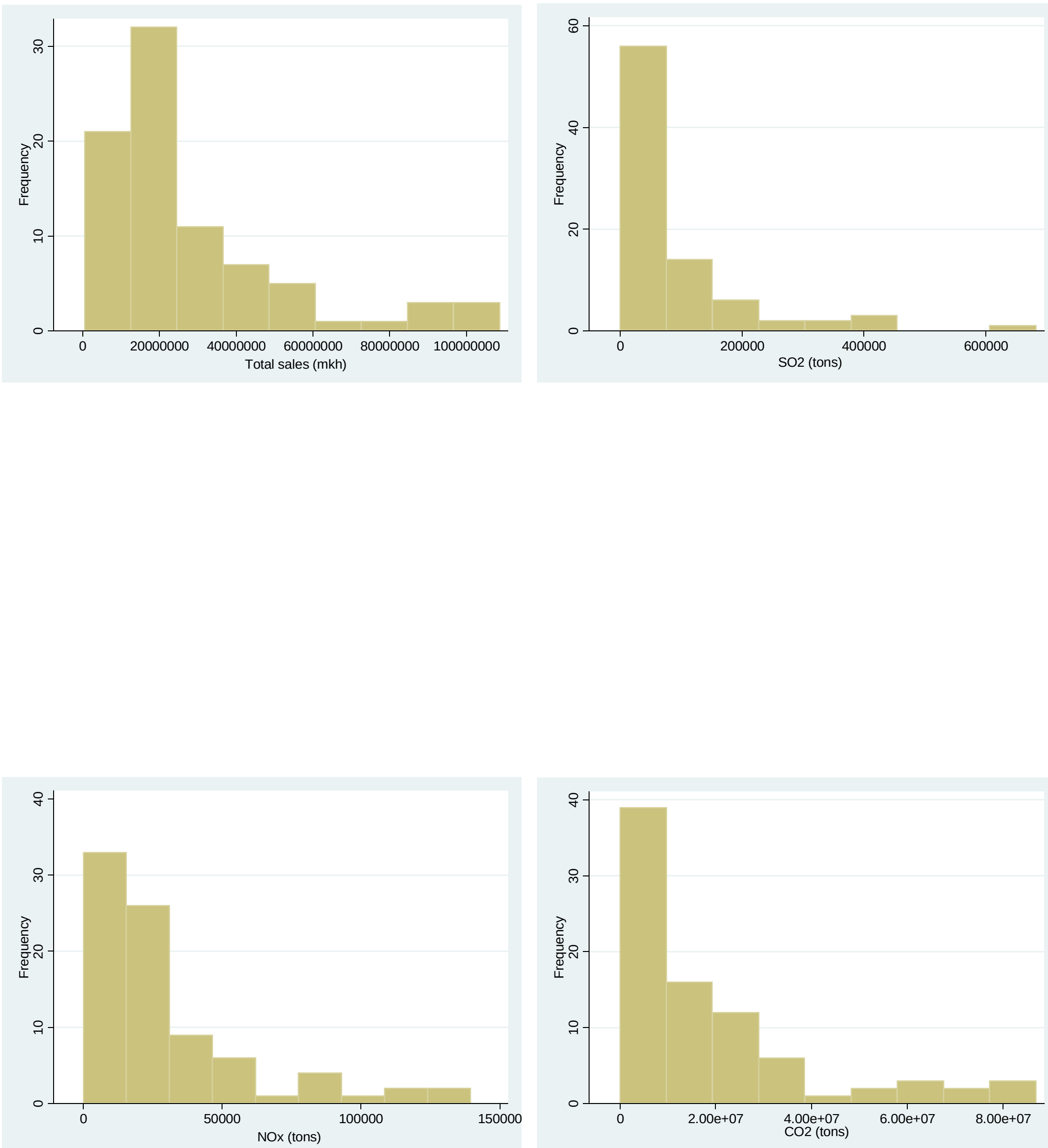


Figure 4 Histograms of the total sales and three types of undesirable outputs

Table 1 Modeling assumptions and ranges of scores

Efficiency measures	Assumptions on undesirable outputs	Range of scores	Source
UINP model	Treated as inputs	[1,∞)	Berg et al. (1992)
Hyperbolic efficiency model	Weakly disposable	[1,∞)	Färe et al. (1989):
Directional distance function	Weakly disposable	[0,∞)	Chambers et al. (1998)
Seiford and Zhu's model	Strongly disposable	[1,∞)	Seiford and Zhu (2002)

Table 2 Summary statistics (n=84)

Variable	Mean	Std. Dev.	Min	Max
Inputs (in dollars)				
Plant value	6.37e+09	7.22e+09	1.65e+08	4.21e+10
Total operation and maintenance expenditure	1.50e+09	1.51e+09	5.53e+07	8.23e+09
Labor cost	1.51e+08	1.96e+08	1450388	9.41e+08
Electricity purchased (MWH)	8818721	8215687	86797	4.60e+07
Output				
Total sales (MWH)	2.73e+07	2.46e+07	121302	1.09e+08
Undesirable outputs (in tons)				
SO_2	79998.26	115548.4	7.108	682271
NO_x	28142.06	30794.87	47.10725	139549.9
CO_2	1.95e+07	2.13e+07	51480.4	8.68e+07
Eco-efficiency	0.2873	0.2782	0.0000	0.7002
Productive efficiency	0.3898	0.2951	0.0000	0.9243
Productive/Eco-efficiency ratio	1.1191	0.2858	0.5882	1.9088

Table 3 Efficiency scores from different models (S1: Baseline scenario, S2: Double SO_2, and S3: Double all undesirable outputs)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Firm	UINP			Hyperbolic			DDF			SZ			Eco-efficiency model		
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
1	1.14	1.14	1.27	1.09	1.00	1.14	19880	1.00	16248	1.28	1.28	1.28	1.37	1.62	2.12
2	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.98	1.98	1.98	1.00	1.00	1.00
3	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
4	1.11	1.14	1.20	1.00	1.00	1.00	1.00	1.00	1.00	3.74	3.74	3.74	1.55	1.80	2.30
5	1.00	1.00	1.10	1.00	1.00	1.07	1.00	1.00	8129	1.28	1.28	1.28	1.00	1.00	1.70
6	1.17	1.17	1.34	1.00	1.00	1.00	1.00	1.00	1.00	1.62	1.62	1.62	1.54	1.79	2.29
7	1.60	1.86	1.92	1.43	1.41	1.64	4080	4860	7301	2.04	2.04	2.04	1.66	1.91	2.41
8	1.00	1.21	1.24	1.00	1.01	1.00	1.00	7.31	1.00	1.97	1.97	1.97	1.00	1.26	1.76
9	1.11	1.11	1.11	1.00	1.00	1.00	1.00	1.00	1.00	1.11	1.11	1.11	1.66	1.91	2.41
10	1.04	1.18	1.28	1.03	1.03	1.15	1270	3366	3083	2.76	2.76	2.76	1.46	1.71	2.21
11	1.48	1.48	1.52	1.31	1.00	1.22	22358	1.00	1.00	1.47	1.47	1.48	1.61	1.86	2.36
12	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.63	1.63	1.63	1.00	1.00	1.00
13	1.49	1.67	1.72	1.33	1.00	1.46	59260	1.00	1.00	1.51	1.51	1.51	1.56	1.81	2.31
14	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.14	1.14	1.14	1.00	1.00	1.00
15	1.34	1.40	1.40	1.00	1.00	1.00	1.00	1.00	1.00	1.30	1.30	1.31	1.63	1.88	2.38
16	1.00	1.02	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.87	1.87	1.87	1.00	1.32	1.82
17	1.74	1.82	1.82	1.00	1.00	1.00	13960	1.00	1.00	1.49	1.49	1.50	1.70	1.95	2.45
18	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
19	1.27	1.44	1.70	1.11	1.23	1.00	2466	21251	1.00	1.67	1.67	1.67	1.35	1.60	2.10
20	1.31	1.49	1.85	1.09	1.00	1.34	31746	1.00	61426	1.76	1.76	1.76	1.48	1.73	2.23
21	1.34	1.35	1.53	1.12	1.00	1.00	5809	1.00	1.00	1.54	1.54	1.54	1.48	1.73	2.23

Firm	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	UINP			Hyperbolic			DDF			SZ			Eco-efficiency model		
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
22	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.69	1.69	1.69	1.00	1.00	1.00
23	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
24	1.00	1.00	1.26	1.00	1.00	1.00	1.00	1.00	1.00	1.24	1.24	1.24	1.00	1.00	1.85
25	1.02	1.21	1.24	1.00	1.00	1.00	1.00	7358	1.00	1.19	1.19	1.19	1.16	1.42	1.92
26	1.08	1.08	1.19	1.00	1.00	1.00	1.00	1.00	1.00	1.59	1.59	1.59	1.41	1.66	2.16
27	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
28	1.00	1.01	1.16	1.00	1.00	1.02	1.00	1.00	2029	1.10	1.10	1.10	1.00	1.00	1.44
29	1.49	1.57	1.61	1.24	1.20	1.40	17175	12687	22681	1.51	1.52	1.52	1.59	1.84	2.34
30	1.01	1.08	1.08	1.00	1.06	1.00	1.00	11010	1.00	1.08	1.08	1.08	1.15	1.47	1.97
31	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
32	1.10	1.10	1.13	1.00	1.00	1.00	1.00	1.00	1.00	1.12	1.12	1.13	1.43	1.68	2.18
33	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.02	1.02	1.02	1.00	1.00	1.00
34	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
35	1.57	1.75	2.26	1.41	1.00	1.55	517	1.00	774	1.69	1.69	1.70	1.67	1.92	2.42
36	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
37	1.19	1.45	1.45	1.00	1.00	1.00	13758	14948	1.00	1.24	1.24	1.24	1.52	1.77	2.27
38	1.25	1.53	1.53	1.00	1.00	1.00	7664	11482	1.00	1.46	1.46	1.46	1.52	1.77	2.27
39	1.05	1.43	1.52	1.00	1.00	1.00	11295	1.00	1.00	1.06	1.06	1.06	1.36	1.61	2.11
40	1.69	1.94	2.08	1.00	1.00	1.00	7688	1.00	1.00	1.74	1.74	1.76	1.66	1.91	2.41
41	1.00	1.01	1.12	1.00	1.00	1.00	1.00	1.00	1.00	1.97	1.97	1.97	1.00	1.00	1.32
42	1.00	1.12	1.31	1.00	1.00	1.00	1.00	1.00	1.00	1.43	1.43	1.43	1.00	1.32	1.82
43	1.54	1.71	2.15	1.36	1.00	1.33	1943	1.00	1.00	2.27	2.27	2.27	1.69	1.94	2.44
44	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.29	2.29	2.29	1.00	1.00	1.00

Firm	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	UINP			Hyperbolic			DDF			SZ			Eco-efficiency model		
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
45	1.61	1.61	1.61	1.38	1.41	1.00	1.00	1.00	1.00	1.56	1.57	1.57	1.70	1.95	2.45
46	1.50	1.66	1.86	1.00	1.00	1.00	40518	52821	74327	1.96	1.97	1.97	1.61	1.86	2.36
47	1.25	1.31	1.31	1.00	1.00	1.00	1.00	1.00	1.00	1.25	1.25	1.25	1.70	1.95	2.45
48	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
49	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
50	1.22	1.26	1.36	1.03	1.06	1.17	10187	15690	1754	1.46	1.46	1.46	1.34	1.59	2.09
51	1.09	1.29	1.33	1.08	1.14	1.17	128.44	145.33	250	2.31	2.31	2.31	1.41	1.66	2.16
52	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.42	2.42	2.42	1.00	1.00	1.00
53	1.33	1.36	1.36	1.09	1.22	1.00	265.11	38809	1.00	1.39	1.39	1.39	1.51	1.76	2.26
54	1.34	1.34	1.41	1.00	1.00	1.00	1.00	1.00	1.00	1.47	1.47	1.47	1.67	1.92	2.42
55	1.03	1.11	1.11	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.63	1.88	2.38
56	1.11	1.24	1.38	1.08	1.13	1.23	4006	6585	7321	1.69	1.69	1.69	1.32	1.57	2.07
57	1.45	1.52	1.52	1.29	1.36	1.46	12980	24872	1830	1.73	1.74	1.74	1.59	1.84	2.34
58	1.00	1.00	1.07	1.00	1.00	1.00	1.00	1.00	1.00	1.05	1.05	1.05	1.00	1.00	1.77
59	1.46	1.94	2.35	1.00	1.00	1.00	1.00	1.00	1.00	2.10	2.10	2.11	1.68	1.93	2.43
60	1.16	1.28	1.43	1.00	1.03	1.00	5448	8685	9570.58	1.73	1.73	1.73	1.41	1.66	2.16
61	1.21	1.45	1.53	1.16	1.14	1.30	14724	13563	15337	1.49	1.49	1.49	1.48	1.73	2.23
62	1.00	1.00	1.07	1.00	1.00	1.00	1.00	1.00	1.00	1.39	1.39	1.40	1.00	1.00	1.74
63	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	2.18	2.18	2.18	1.00	1.00	1.00
64	1.58	1.83	2.01	1.37	1.40	1.53	4271	6690	6462	2.39	2.39	2.39	1.70	1.95	2.45
65	1.26	1.26	1.49	1.09	1.00	1.34	9466	1.00	17391	1.51	1.51	1.52	1.47	1.72	2.22
66	1.00	1.14	1.20	1.00	1.00	1.00	1.00	1.00	1.00	2.36	2.36	2.36	1.00	1.31	1.84
67	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
68	1.0	1.1	1.2	1.0	1.0	1.0	1.00	1.00	1.00	1.3	1.3	1.3	1.34	1.59	2.09

Firm	UINP			Hyperbolic			DDF			SZ			Eco-efficiency model		
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
	4	3	0	0	0	0				5	5	5			
69	1.01	1.28	1.33	1.00	1.00	1.00	1.00	1.00	1.00	1.26	1.26	1.26	1.23	1.48	1.98
70	1.44	1.60	1.60	1.00	1.00	1.00	1.00	1.00	1.00	1.71	1.72	1.72	1.51	1.76	2.26
71	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
72	1.00	1.00	1.03	1.00	1.00	1.00	1.00	1.00	1.00	1.03	1.03	1.03	1.00	1.00	1.87
73	1.00	1.02	1.10	1.00	1.00	1.00	1.00	1.00	1.00	1.67	1.67	1.67	1.00	1.00	1.00
74	1.34	1.46	1.73	1.19	1.19	1.43	34713	38341	61410	1.69	1.69	1.69	1.46	1.71	2.21
75	1.00	1.01	1.05	1.00	1.00	1.00	1.00	1.00	1.00	1.41	1.41	1.41	1.00	1.09	1.59
76	1.30	1.52	1.77	1.12	1.19	1.00	1819	5461	1.00	1.64	1.64	1.65	1.41	1.66	2.16
77	1.58	1.79	1.93	1.33	1.00	1.00	3949	1.00	1.00	1.81	1.81	1.81	1.66	1.91	2.41
78	1.52	1.72	2.07	1.34	1.30	1.61	7376	7864	12565	1.87	1.87	1.87	1.59	1.84	2.34
79	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
80	1.10	1.10	1.10	1.00	1.00	1.00	1.00	1.00	1.00	1.08	1.08	1.09	1.50	1.75	2.25
81	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
82	1.00	1.00	1.19	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
83	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
84	1.00	1.02	1.02	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Avg.	1.17	1.25	1.33	1.06	1.04	1.08	4414	3649	3928	1.51	1.51	1.51	1.29	1.44	1.81
STD.	0.21	0.28	0.35	0.12	0.10	0.17	10017	9268	12788	0.49	0.50	0.50	0.28	0.38	0.58

APPENDIX A: Existing models to efficiency measurement in the presence of undesirable outputs

Undesirable outputs treated as inputs (UINP) model

In the UINP model, undesirable outputs are modeled as production inputs (e.g., Berg et al. 1992; Lee et al. 2002; Haliu and Veenam 2001). The UINP efficiency score can be obtained from

$$\begin{aligned}
&Max \quad \mathrm{e} \\
&s.t. \quad \sum_{k=1}^{K} z_k x_{km} \le x_m, \text{ for } m = 1,..,M \qquad (5\text{-}1)\\
&\qquad \sum_{k=1}^{K} z_k d_{kn} \ge e d_n, \text{ for } n = 1,..,N \qquad (5\text{-}2)\\
&\qquad \sum_{k=1}^{K} z_k u_{kp} \le u_p, \text{ for } p = 1,..,P \qquad (5\text{-}3)\\
&\qquad z_k \ge 0, \text{ for } k = 1,...,K \qquad (5\text{-}4)
\end{aligned}$$

One of the weaknesses of the UINP formulation is that using fixed amount of inputs can produce an unbounded amount of undesirable outputs in the technology set, which is impossible in practice (Färe and Grosskopf 2003). The UINP model is also unrepresentative of the real production process because outputs are modeled as inputs (Seiford and Zhu 2002; Kuosmanen 2005).

The hyperbolic model and directional distance function

The hyperbolic productive efficiency measure was first proposed by Färe et al. (1989). In the hyperbolic model efficiency is achieved by proportionally expanding desirable and contracting undesirable outputs at the same time. Therefore the locus of projecting one production unit to the efficient frontier will be hyperbolical. The formulation proposed by Färe et al. (1989) is below:

$$\begin{aligned}
&H_{output}(x,d,u) := \max \beta \\
&\text{s.t.} \quad \sum_{k=1}^{K} z_k x_{km} \le x_{1m}, \text{for } m = 1,..,M \qquad (6\text{-}1)\\
&\qquad \sum_{k=1}^{K} z_k d_{kn} \ge \beta \; d_{1n}, \text{ for } n = 1,..,N \qquad (6\text{-}2)\\
&\qquad \sum_{k=1}^{K} z_k u_{pk} = u_{1p} / \beta \;, \text{for } p = 1,..,P \qquad (6\text{-}3)\\
&\qquad z_k \ge 0, \text{ for } k = 1,...,K \qquad (6\text{-}4)
\end{aligned}$$

In the above formulation, undesirable outputs are introduced in (4-3) with an equality constraint. The equality sign is used to impose the weakly disposable assumption on undesirable outputs. Using a comparable model, Chambers et al. (1997) applied the Directional Distance Function (DDF) to evaluating production performance in the presence of both desirable and undesirable outputs, which can be obtained by solving the following problem:

$$D_{output}(x,d,u,g_n^d,g_p^u) := \max \beta$$

$$\text{s.t.} \quad \sum_{k=1}^{K} z_k x_{km} \le x_{1m}, \text{for m} = 1,..,\text{M} \qquad (7\text{-}1)$$

$$\sum_{k=1}^{K} z_k d_{kn} \ge d_{1n} + \beta g_n^{\text{d}}, \text{ for n} = 1,..,\text{N} \qquad (7\text{-}2)$$

$$\sum_{k=1}^{K} z_k u_{kp} = u_{1p} - \beta g_p^u, \text{for p} = 1,..,\text{P} \qquad (7\text{-}3)$$

$$z_k \ge 0, \quad \text{for } k = 1,...,K \qquad (7\text{-}4)$$

In the above model, the efficiency score shows the potential to increasing desirable while simultaneous cutting undesirable outputs in the predetermined direction (g_n^d , g_p^u). The DDF model has been widely used in various evaluation problems, including banks, electricity industries, paper mills, industry efficiency, provincial governments, agriculture, transportation agencies and airports (Lee et al. 2002; Picazo-Tadeo et al. 2005; Park and Webber 2006; Färe et al. 2007; McMullen and Noh 2007; Watanabe and Tanaka 2007; Pathomsiri et al. 2008; Yu et al. 2008; Mukherjee 2009).

Despite the popularity of the DDF model, the approach has several limitations. First, to implement the DDF approach, one needs to specify a directional vector from the firm to the frontier before computing efficiency scores. This would only be appropriate if (1) we had sufficient information about the transformation ratio between desirable and undesirable outputs, and if (2) all evaluated firms followed this fixed direction pattern to gain efficiency. Yet in practice these conditions cannot be easily satisfied or even verified. Moreover, as note in Färe and Grosskopf (2004), "…*clearly [the directional] efficiency depends on the choice of the directional vector (p.9)…However, we do not have a general rule for determining those vectors (p.10).*" Empirical applications of DDF in the literature all designate directional vectors in an ad hoc manner. These choices are made at the risk of research validity. Another problem is that the value of the DDF will depend on the measurement unit of outputs (e.g., in pounds, kg, or tons; or in Euros or dollars). This can place a major restriction on interpreting and comparing the DDF efficiency scores.

Seiford and Zhu's [SZ] model

The model developed by Seiford and Zhu (2002) deals with undesirable outputs by transforming the output data. In their model, undesirable outputs are first multiplied by minus one, and then translated back to positive value again by adding them with a constant vector. Efficiency is measured by the expansion factor for the desirable output and the transformed undesirable output. Specifically,

$$
\begin{aligned}
& \max \ h \\
\text{s.t.} \quad & \sum_{k=1}^{K} z_k x_{km} \le x_{1m}, \ \text{for m} = 1,..,\text{M} && \text{(8-1)} \\
& \sum_{k=1}^{K} z_k d_{kn} \ge h d_{1n}, \ \text{for n} = 1,..,\text{N} && \text{(8-2)} \\
& \sum_{k=1}^{K} z_k u'_{kp} \ge h u'_{1p}, \ \text{for p} = 1,..,\text{P} && \text{(8-3)} \\
& z_k \ge 0, \ \text{ for } k = 1,\dots,K && \text{(8-4)}
\end{aligned}
$$

where $u'_{kp} = -u_{kp} + \omega_p > 0$ and ω_p is a sufficiently large number.

It is important to note that, although the SZ model is unit-invariant, its efficiency score cab be influenced by the value of the translation vector ω_p .

APPENDIX B: Illustrative examples: assessing the eco-efficiency of paper mills

The data used in this section consist of the empirical inputs and outputs of 30 paper mills; this data set also appears in Färe et al. (1989) and Seiford and Zhu (2002). This example uses four inputs (fiber, energy, capital and labor) to produce one desirable output (paper) and four undesirable outputs (biochemical oxygen demand, total suspended solids, particulates and sulfur oxides). See Table 4 for descriptive statistics of the data. The experimental results can be found in Table 5 below (note that the eco-efficiency score is augmented by one for easier comparison). For this dataset we still identify the same problems that we observed for the data of electric utility firms.

Table 4 Descriptive statistics of the paper mill data (n=30)

Variable	Mean	Std. Dev.	Min	Max
Fiber	103997.20	65671.23	14743.00	312910.00
Energy	2285863.00	1415598.00	304031.00	5771544.00
Capital	78500000.00	49700000.00	18100000.00	262000000.00
Labor	1107302.00	767867.10	163993.00	3144336.00
Paper	106615.60	65494.73	1800.00	293000.00
Biochemical oxygen demand (BOD)	3014.00	3376.71	86.79	13318.19
Total suspended solids	1807.54	1896.37	17.38	9015.50
Particulates	327.23	596.22	2.84	2284.27
SOx	2730.19	3136.69	1.26	12129.65

Table 5 Efficiency scores from different models (S1: Baseline scenario, S2: Double biochemical oxygen demand, and S3: Double all undesirable outputs)

	UINP model			Hyperbolic			DDF			SZ model			Eco-efficiency		
mill	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3	S1	S2	S3
1	1.14	1.14	1.21	1	1	1	1	1	1	1.0	1.0	1.0	1.6	1.6	1.7

	UINP model			Hyperbolic			DDF			SZ model			Eco-efficiency		
2	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
3	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
4	1.04	1.04	1.19	1	1	1	1	1	1	1.0	1.0	1.0	1.4	1.4	1.6
5	1.47	1.47	1.50	1.3	1.3	1.3	16.19	16.1	34.1	1.0	1.0	1.0	1.6	1.7	1.7
6	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
8	1.24	1.39	1.39	1	1	1	1	1	1	1.0	1.0	1.0	1.7	1.7	1.7
9	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
10	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
11	1.12	1.13	1.14	1	1	1	1	1	1	1.0	1.0	1.0	1.7	1.7	1.7
12	1.15	1.15	1.16	1	1	1	1	1	1	1.1	1.1	1.1	1.7	1.7	1.8
13	1.54	1.54	1.54	1	1	1	1	1	1	1.0	1.0	1.0	1.6	1.7	1.7
14	1.22	1.22	1.27	1.1	1	1	181.7	1	1	1.0	1.0	1.0	1.6	1.6	1.7
15	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
16	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
17	13.6	13.6	14.2	1	1	1	1	1	1	1	1	1	4.0	4.1	4.1
18	14.1	14.2	14.3	1	1	1	1	1	1	1	1	1	4.0	4.0	4.1
19	1.47	1.47	1.47	1	1	1	1	1	1	1.1	1.1	1.1	1.8	1.8	1.8
20	1.85	1.85	1.85	1.1	1	1	1	1	1	1.0	1.0	1.1	1.7	1.7	1.8
21	1.03	1.03	1.04	1	1	1	1	1	1	1	1	1	1.6	1.6	1.7
22	1.30	1.30	1.34	1	1	1	1	1	1	1.0	1.0	1.0	1.7	1.7	1.7
23	1.29	1.29	1.31	1	1	1	1	1	1	1.0	1.0	1.0	1.6	1.6	1.7
24	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
25	1.05	1.05	1.11	1	1	1	1	1	1	1	1	1	1.3	1.4	1.5
26	1.06	1.06	1.13	1	1	1	1	1	1	1.0	1.0	1.0	1.5	1.5	1.6
27	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
28	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
29	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
30	1.09	1.09	1.12	1	1	1	1	1	1	1.0	1.0	1.0	1.6	1.6	1.7
Avg	1.99	2.00	2.05	1.0	1.0	1.0	7.57	1.50	2.10	1.0	1.0	1.0	1.5	1.5	1.6
Std.	3.24	3.26	3.35	0.0	0.0	0.0	33.0	2.76	6.05	0.0	0.0	0.0	0.7	0.7	0.7

APPENDIX C: Mathematical Proofs

Proof of Theorem 1: For all firms $k=1,...,K$, we first substitute input i and output n, respectively by

$\tilde{x}_{ki}=\alpha x_{ki}$ and $\tilde{d}_{kn}=\beta d_{kn}$, where α and β are arbitrary positive numbers. For input i, it is straightforward to prove the homogeneity, since form Equation (2-2) we can derive

$$\sum_{k=1}^{K} z_k \tilde{x}_{ik} \le \tilde{x}_{ik} \Rightarrow \alpha \sum_{k=1}^{K} z_k x_{ik} \le \alpha x_{ik} \Rightarrow \sum_{k=1}^{K} z_k x_{ik} \le x_{ik} \tag{9}$$

For output n, observe first that the term associated with this output in the objective function (2-1) is now rewritten as $\tilde{g}_i^d / \tilde{d}_{ki} = (\tilde{g}_i^d / \beta)/d_{ki}$. In addition, in Equation (2-3), we obtain

$$\sum_{k=1}^{K} z_k \tilde{d}_{kn} \le \tilde{d}_{kn} + \tilde{g}_n^d \Rightarrow \beta \sum_{k=1}^{K} z_k d_{kn} \le \beta d_{kn} + \tilde{g}_n^d \Rightarrow \sum_{k=1}^{K} z_k d_{kn} \le d_{kn} + \tilde{g}_n^d / \beta . \tag{10}$$

Since in model (2) we restrict that $\tilde{g}_n^d \ge 0$, it follows that $\tilde{g}_n^d / \beta \ge 0$. By observing $\tilde{g}_k^d / \beta$ in (2-1) and (2-3), we can obtain problem (2) in its original form. The homogeneous property of undesirable outputs can be proved analogously. □

Proof of Theorem 2: Consider an arbitrary input output vector $(x,d,u) \in \Omega \subset \Re^{M \times N \times P}$. Without loss of generality, suppose that (x,d,u) is dominated by some $(x,d',u') \in \Omega$. Then there must exist a N-by-P non-negative vector $(g^d, g^u) \ne 0$, for which $(x,d',u') = (x, d+g^d, u-g^u)$.

It follows that there must also exist nonnegative $z=(z_1,...,z_k)$ satisfying

$$\sum_{m=1}^{M} z_k x_{km} \le x', \sum_{n=1}^{N} z_k d_{kn} \ge d', \text{ and } \sum_{p=1}^{P} z_k u_{kp} = u' \tag{11}$$

, which shows that (z, g^d, g^u) is a feasible solution to the eco-efficiency model (2). Given that $(g^d, g^u) \ne 0$, we obtain $E(x,d,u) > 0$, where $E(.)$ is defined in (2).

Conversely, we can show that when $E(\alpha, \beta, \gamma) > 0$, the optimal solution (z^*, g^{d^*}, g^{u^*}) can be used to construct a vector $(x, d'', u'') = (x, d + g^{d^*}, u - g^{u^*}) \in \Omega$, which dominates (x, d, u).

[1] See Freudenburg (2005) Figure 3b page 99.

[2] Tyteca (1998) and Zhou et al. (2007) have adopted similar efficiency measures.

[3] The same experiment was conducted using paper mill data from Färe et al. (1989) and Seiford and Zhu (2002). Results were similar and are presented in Appendix B.

[4] See http://www.epa.gov/airmarkets/progsregs/arp/index.html. Other related programs include the NO_x Trading Program and the Clean Air Interstate Rule.

[5] Specifically, all firms in the sample will become efficient when the hyperbolic, DDF, and SZ models are applied to the dummy data; for the input model, the efficiency will remain unchanged when the dummy data are used.

[6] Efficiency scores are presented in Appendix A.

[7] The skewness of the desirable output (total sales) is 1.6641, while those of the undesirable outputs (SO_2, NO_x, and CO_2) are 2.6926, 1.8318, and 1.6973, respectively.

[8] It is estimated that almost 11 percent of the assets under professional management in the United States are invested with social responsibility in mind (Source: Social Investment Forum, 2007).

[9] The mean ratio is 1.12 and the standard deviation is 0.29 (see Table 2).