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Invited paper

Malmquist productivity index for multi-output producers: An application to electricity generation plants

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ABSTRACT

Different types of plants are used to generate electricity in the US: single-, multi-, and mixed-electricity plants. In this paper, we question the best type/design of plants for both renewable and non-renewable electricity. To do so, we suggest a new index that takes the form of a Malmquist productivity index. The specificity of our new index is that it offers the option to investigate the performances and the causes of the performance changes for each type of electricity separately; this is not possible when relying on more standard indexes. Moreover, our new index takes the links between the inputs and the outputs into account, and is nonparametric in nature. Using our index, we study the performances of more than 5000 plants for the period 2000–2012. Our findings reveal that single-electricity plants perform better for renewable electricity, while multi-electricity plants perform better for non-renewable electricity. This is coherent with the decreasing importance of multi-electricity plants in the US, and the increasing importance of single-electricity plants producing renewable electricity. Furthermore, our results do not suggest that combining renewable and non-renewable electricity generations within a plant improves the performance of the plants. Finally, we demonstrate that the reasons for the changes in performance are different for each type of electricity and plant.

1. Introduction

In the US, there are different types of electricity generation plants that we can group into three main categories. Firstly, those that produce only one type of (renewable or non-renewable) electricity. Next, those that produce more than one type of (renewable or non-renewable) electricity. Finally, those that produce both renewable and non-renewable electricity. The economic motivation to produce more than one type of electricity may be due to the cost aspect of the production process. Indeed, it is less costly to produce multiple types of electricity within a large plant rather than in several small plants. Or in other words, the plants benefit from economies of scope (such as infrastructure or knowledge) by producing multiple outputs.[1] Improving the performances of those large plants is therefore an important goal, which both regulators and managers are trying to achieve.

In this paper, we question the best design of the plants for renewable and non-renewable electricity generation. That is, we compare the three different types of plants and identify the best one. In other words, we ask the following questions: Is it preferable to have single- or multi-electricity plants? Should plants focus on the production of renewable or non-renewable electricity or produce both? Moreover, we are interested in the reasons for the performance differences. We could point out two main causes: efficiency and technical changes. Efficiency change reveals how the plants use their current technology to generate the electricity. Technical change reveals how the plants have succeeded in the innovation of the production process. Clearly, it is not obvious that the cause for the performance changes is the same for each type of electricity production and for every type of plant. The Environmental Protection Agency in the US has developed a complete and very detailed database for more than 5000 plants for the period 2000–2012. This represents a unique opportunity to study the performances of electricity plants in the US, and in particular, to question the design of the plants.

To answer our questions, we will develop a new nonparametric technical index and its decomposition into technical and efficiency changes for multi-output producers. The new technical index takes the form of a Malmquist productivity index (MPI). Our new MPI is specially designed for the kind of producers considered in the application. Firstly, the links between the inputs and the outputs are taken into account. Indeed, plants use inputs that are differentially linked to each type of electricity production. Next, the methodology we have developed allows us to define and decompose output-specific MPIs. We believe that these output-specific indexes are of particular interest in this context, since they will allow us to propose results for each type of electricity

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[1] Economies of scope, a term popularized by Panzar and Willig [57], are present when it is less costly to produce multiple outputs within a firm rather than in several firms.

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separately. This is not possible when considering standard MPI models. Finally, the MPI is nonparametric in nature since it is not based on any parametric/functional specifications of the production technology.[2] Rather, we reconstruct the production possibilities solely using the observed inputs and outputs. In this context, we believe that the nonparametric feature of the index is particularly relevant since it is very difficult to impose a specific production function for the multi-output plants and, importantly, this may have a huge impact on the results.

Below we present a literature review on the MPI and the links between the inputs and the outputs. This will allow us to position our contribution to the relevant literature.

1.1. Malmquist productivity index

The Malmquist productivity index (MPI) proposed by Caves et al. [1] who named it after Malmquist [2]; measures relative performance changes of Decision Making Units (DMUs) between two or more periods. The MPI has several desirable features. On the one hand, the MPI could be computed using the distances to the reconstructed production possibilities obtained with the nonparametric efficiency analysis. It implies that no assumption about production functions are made. On the other hand, the MPI can be decomposed into two different components, efficiency changes and technical changes, to better understand the causes of relative performance change. Several decompositions have been suggested by Färe et al. [3,4], and Ray and Desli [5]. Finally, the MPI requires only input and output data; no price data are needed.

Since the initial definition of the MPI, several theoretical extensions have been proposed [6]. Suggested a new decomposition of the MPI to account for changes in plant capacity utilization; Chen [7] introduced a non-radial MPI; Chen and Ali [8] provided a further discussion on its second component; Pastor and Lovell [9] proposed a global MPI; Camanho and Dyson [10] suggested to using the MPI to compare groups; Zelenyuk [11] developed an aggregate MPI to compare groups; Yu [12] provided a new decomposition of the MPI that measures capacity productivity change and variable input productivity change; Kao [13] proposed a common-weight DEA model for the global MPI; Oh and Lee [14] introduced a metafrontier approach of the MPI when the technologies of the DMUs are not the same; Portela and Thanassoulis [15] explained how to use MPI with negative data; Pastor, Asmild and Lovell [16] introduced a biennial MPI; Wang and Lan [17] suggested a double frontier MPI; O'Donnell [18] defined complete productivity indexes; Kao and Hwang [19] defined a multi-period MPI to capture the productivity change for a large period; and Yang et al. [20] introduced a factor-specific MPI based on common weights DEA. All the above theoretical extensions and the large numbers of applications clearly reveal the usefulness of the MPI as a theoretical and practical instrument.

Initially the MPI, as defined by Caves et al. [1], was interpreted as a productivity change index. Recently, there has been a debate on the validity of the MPI to measure productivity change. Indeed, this is only true under quite restrictive conditions. On the one hand, it requires that the technology is inversely homothetic (intuitively, it implies separability between inputs and outputs, see Färe et al. [21] for details), which could be a stringent condition. On the other hand, the MPI is not complete (intuitively, it means that it could not be written as a function of aggregate inputs and outputs). We refer to O'Donnell [18,22] and Peyrache [64] who highlight this issue. Contrary to the MPI, there exists other productivity indexes, like the Laspeyres, Paasche, Fisher, Tornqvist and Hicks-Moorsteen (introduced by Diewert and Nakamura [23], and Bjurek [24]) indexes, which, in general, measure productivity changes more adequately. Nevertheless, the MPI is still the most popular index used in practice, probably due to its decomposition. Therefore, in the following, we do not claim that the MPI is a productivity change index. On the contrary, we interpret the MPI as a relative performance index (this is also the interpretation used by Grosskopf [25]) and use its decomposition into efficiency and technical changes. As a final remark, it is important to stress that the output-specific modelling proposed here does not crucially depend on the MPI and could fairly easily be used in the context of other indexes.

While the standard MPI and its extensions have demonstrated their usefulness in capturing the relative performance change of the DMUs, these models quite often suffer from a lack of realism in multi-output settings. We can point to two main limitations in those settings. Firstly, standard MPI models consider that all the inputs produce simultaneously all the outputs (i.e. a black box modelling), while in multi-output settings every inputs could be allocated differently to each output production. Secondly, standard MPI models only provide results for the aggregate production process. In multi-output settings, regulators and managers require more detailed results (i.e. results for each output production process) to make appropriate decisions.

1.2. Links between inputs and outputs

In multi-output settings, different types of inputs are simultaneously used to produce the outputs. On the one hand, some inputs are jointly used to produce all (or a subset of) the outputs (see Salerian and Chan [26]; Despic et al. [27]; and Cherchye et al. [28]). These inputs give rise to economies of scope, which form a prime economic motivation to produce multiple outputs. On the other hand, some inputs can also be allocated to specific output productions (see Ref. [29]; Färe et al. [30]; Tone and Tsutsui [31]; Cherchye et al. [32]; and Walheer [33,34]). By integrating information on the internal production structure, all the above approaches are trying to enhance the realism of the efficiency analysis. As such, these approaches have a greater ability to detect inefficiency (i.e. more discriminatory power) than more standard techniques that do not use this information. The model of Cherchye et al. [35,36] provides a unifying framework, which considers both types of inputs. They model each output separately by its own production technology, while allowing for interdependence between the output-specific technologies. As a consequence, the links between inputs and outputs are naturally taken into account. Attractively, their model does not require any extra assumptions about the production process (only the production axioms of standard efficiency models adapted to their output-specific modelling).

While these approaches have been used in different contexts and prove their usefulness, they only propose a static analysis of the multi-output production processes.[3] In this paper, we extend their methodology in a dynamic setting by suggesting a new index, which takes the form of an MPI. Attractively, the output-specific modelling of the production process naturally allows us to define output-specific MPIs and their decomposition into output-specific efficiency change and output-specific technological change. As such, the proposed methodology has more discriminatory power and gives more detailed results than standard MPI approaches. As a final remark, we point out that the index we suggest bears a close relationship to an existing index in the literature. Indeed, Walheer [37,38] has also proposed a productivity index for multi-output settings. The main difference with our index is that he assumes that the DMUs are cost minimizers while we adopt a technical perspective and focus our attention on the decomposition of the index into efficiency and technical changes.

[2] At this point it should be made clear that the MPI is nonparametric in this paper only because we use the nonparametric efficiency model to estimate the distance functions. There exists parametric estimators too. See for example, Fuentes et al. [58] for more discussion. Refer to Färe et al. [59]; Cooper et al. [60]; Cooper et al. [61]; Fried et al. [62]; and Cook and Seiford [63] for reviews on the nonparametric efficiency approach.

[3] For applications, see, for example, Cherchye et al. [32] and Cherchye et al. [36] who apply the methodology to the case of a large service company; Cherchye et al. [35] who apply the methodology to the case of pollutant plants; and Walheer [33,34] who apply the methodology to the case of the growth and the convergence of countries.

1.3. Outline

The rest of this paper unfolds as follows. Section 2 presents the methodology. In Section 3, we apply the methodology to the case of electricity plants in the US. Section 4 concludes.

2. Methodology

In this section, we start by introducing some necessary notation and terminology. Next, we present our output-specific and overall technical efficiency measurements and indicate how to compute them in practice. Finally, we define our output-specific and overall MPIs and their decompositions.

2.1. Data set and technology sets

Suppose we observe data for n DMUs during T periods. Each DMU $j \in \{1, ..., n\}$ in every period $t \in \{1, ..., T\}$, use m inputs captured by the vector $\mathbf{X}_j = (x_{jt}^1, ..., x_{jt}^m)' \in \mathbb{R}_+^m$, to produce s outputs, captured by the vector $\mathbf{Y}_{jt} = \left(y_{jt}^1, ..., y_{jt}^s\right)' \in \mathbb{R}_+^s$.

Suppose also that the inputs are linked differently to the outputs. Some inputs are only used in the production process of specific outputs, or in other words, these inputs are allocated to individual output r. We use $\alpha_{jt}^r \in [0,1]$ as the share of these inputs that is used to produce output r. Clearly, we have $\sum_{r=1}^s \alpha_{jt}^r = 1$. Some other inputs are simultaneously used in the production process of different outputs and can thus not be allocated to specific outputs. These inputs give rise to economies of scope, which constitutes a prime economic motivation to produce multiple outputs.

Let $\mathbf{X}_{jt}^r \in \mathbb{R}_+^m$ denote the vector of inputs used to produce output r. Clearly, when some inputs cannot be allocated to the production of specific outputs, they will appear in all $\mathbf{X}_{jt}^r$ making the output-specific production processes interdependent. Attractively, the output-specific input vectors $\mathbf{X}_{jt}^r$ can easily be connected with the initial input vector $\mathbf{X}_{jt}$ if the input allocation is observed. Let us define $\mathbf{V}_{jt}^r$ for every DMU j at period t as follows:

$$(\mathbf{V}_{jt}^r)_i = \begin{cases} 1 & \text{if input } i \text{ is used to produce all the outputs,} \\ (\alpha_{jt}^r)_i & \text{if input } i \text{ is allocated to the production of output } r, \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

As such, $\mathbf{V}_{jt}^r$ summarizes the information regarding how the inputs are allocated to output r for DMU j at period t. The output-specific input vectors are therefore obtained as follows: $\mathbf{X}_{jt}^r = \mathbf{V}_{jt}^r \odot \mathbf{X}_{jt}$ (where $\odot$ is the element-by-element product).

We assume that we observe the allocation of the inputs to outputs. That is, we observe $\mathbf{V}_{jt}^1, ..., \mathbf{V}_{jt}^r$, and therefore we also observe the output-specific vectors $\mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^r$. This is not a strong assumption in many contexts since in general the DMUs know how they use their inputs to produce their outputs. Nevertheless, the following methodology is easily extended if the allocation is not or partially observed. See Cherchye et al. [32] and Walheer [33]. Taken together, we observe the following data set D:

$$D = \left\{ \left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s \right) \middle| j = 1, ..., n;\ t = 1, ..., T \right\}. \tag{2}$$

We use input requirement sets $I_t^r\left(y_{jt}^r\right)$ to characterize the technology. In particular, $I_t^r\left(y_{jt}^r\right)$ is defined for every output r as follows:

$$I_t^r\left(y_{jt}^r\right) = \left\{ \mathbf{X}^r \in \mathbb{R}_+^m \middle| \mathbf{X}^r \text{ can produce } y_{jt}^r \right\}. \tag{3}$$

$I_t^r\left(y_{jt}^r\right)$ contains all the combinations of output-specific inputs $\mathbf{X}^r$ that can produce the output quantity y_{jt}^r. As discussed before, the output-specific vectors are interdependent when some inputs cannot be allocated to a specific production process making the input requirement sets $I_t^r\left(y_{jt}^r\right)$ interconnected.

We assume that those sets are monotone (or free-disposal), convex and satisfy variable returns-to-scale. These technology axioms are common to many popular nonparametric efficiency models and form an empirically attractive minimal set of assumptions. Moreover, they make sense for many empirical applications. It is important to remark that the proposed methodology can easily be defined when considering other technology axioms, as for example, non-convexity, constant returns-to-scale, or weak disposability. We refer to Cherchye et al. [32] for a rigorous definition of these technology axioms in a similar context.

2.2. Efficiency measurements

As explained in the Introduction, we are interested by the cost/input side of the plant production process. As such, we evaluate input efficiency as the distance of the evaluated DMU's output-specific input vector to the isoquant $\text{Isoq}I_t^r\left(y_{jt}^r\right)$, which is defined as:

$$\text{Isoq}I_t^r\left(y_{jt}^r\right) = \left\{ \mathbf{X}^r \in I_t^r\left(y_{jt}^r\right) \middle| \text{for } 0 < \beta < 1, \beta\mathbf{X}^r \notin I_t^r\left(y_{jt}^r\right) \right\}. \tag{4}$$

Thus, if $\mathbf{X}_{jt}^r \in \text{Isoq}I_t^r\left(y_{jt}^r\right)$, it means that the inputs $\mathbf{X}_{jt}^r$ are the minimal input quantities needed at time t to produce the output quantity y_{jt}^r. When it is not the case, it implies that the inputs can be reduced, while keeping the output quantity at the same level. $\text{Isoq}I_t^r\left(y_{jt}^r\right)$ is therefore known as the technically efficient frontier of $I^r\left(y_{jt}^r\right)$. We note that the index t on the input requirement set refers to the year of the technology.

A natural indicator of the distance to the isoquant is the radial input distance function introduced by Shephard [39,40].[4] When considering input requirement set r, it is defined as:

$$D_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) = \max\left\{ \phi \middle| \left(\frac{\mathbf{X}_{jt}^r}{\phi}\right) \in I_t^r\left(y_{jt}^r\right) \right\}. \tag{5}$$

$D_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ is the largest equiproportionate factor by which the input quantities $\mathbf{X}_{jt}^r$ can be reduced and still produce the quantity y_{jt}^r. $D_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) \geq 1$, with $D_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) > 1$ reflecting inefficient behaviour for production of the $r-$th output, and $D_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) = 1$ implies efficient behaviour for output r.

The input distance function is reciprocal to the input-oriented technical efficiency, which is known as the Debreu [41] – Farrell [42] input efficiency measure. It is defined as follows:

$$TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) = \min\left\{ \theta \middle| \theta\mathbf{X}_{jt}^r \in I_t^r\left(y_{jt}^r\right) \right\}. \tag{6}$$

$TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ gives the maximal equiproportionate input reduction (captured by $\theta\mathbf{X}_{jt}^r$) that still allows to produce the output y_{jt}^r.

[4] The radial input distance function is the most natural indicator given our application; refer to Cherchye et al. [36] for an extension of the output-specific setting with directional distance functions.

$TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ is situated between 0 and 1, and a greater value of $TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ indicates lower technical inefficiency. A value of one indicates an efficient behaviour.

The output-specific technical efficiency measurement $TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ benchmarks DMUs for each output individually. Below, we explain how the output-specific modelling can be used to benchmark DMUs for the whole production process. This overall technical efficiency measurement, denoted $TE_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$, will provide a complementary benchmarking analysis to the output-specific technical efficiency measurements $TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$.

We start by defining the overall distance function as follows:

$$D_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right) = \max\left\{\nu \,\middle|\, \forall\, r: \left(\frac{\mathbf{X}_{jt}^r}{\nu}\right) \in I_t^r\left(y_{jt}^r\right)\right\}. \tag{7}$$

$D_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$ is a modified version of Shephard's [39,40] definition when considering s output-specific input requirement sets. The interpretation of the distance $D_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$ is analogous to the interpretation of the output-specific distance $D_t(y_t^r, \mathbf{X}_t^r)$, but applies here at the aggregate level: $D_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$ is the largest equiproportionate factor by which the inputs $(\mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s)$ can be reduced and still produce the quantity $\left(y_{jt}^1, ..., y_{jt}^s\right)$.

Using the same relationship as before between the input distance and the input technical efficiency measurement, we can easily define our concept of overall technical efficiency measurement:

$$TE_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right) = \min\left\{\eta \,\middle|\, \forall\, r: \eta\mathbf{X}_{jt}^r \in I_t^r\left(y_{jt}^r\right)\right\}. \tag{8}$$

Again, the interpretation is analogous to the interpretation of the technical efficiency measurement $TE_t^r(y_t^r, \mathbf{X}_t^r)$. That is, $TE_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$ is situated between 0 and 1, and a lower value indicates greater technical inefficiency.

Interestingly, the overall technical efficiency measurement could be related to the output-specific technical efficiency measurements by taking the maximum:

$$TE_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right) = \max_{r\in\{1,...,s\}} TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right). \tag{9}$$

This relationship is explained by the presence of inputs jointly used to produce all the outputs that must, by definition, be reduced by the same proportion for all the outputs. As such, by taking the maximum we are sure that this is the case. It also motivates the need for output-specific results to contrast the results obtained at the aggregate level with the overall technical efficiency measurement.

2.3. Linear programs

In practice, the empirical output-specific and the overall technical efficiency scores are easily obtained by the use of linear programs. The output-specific technical efficiency scores $TE_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right)$ are obtained for each output $r \in \{1, ..., s\}$ of each DMU $j \in \{1, ..., n\}$ at period $t \in \{1, ..., T\}$ by using **(LP-1)**:

$$\begin{aligned}
&\mathrm{TE}_t^r\left(y_{jt}^r, \mathbf{X}_{jt}^r\right) = \min_{\lambda_{kt}^r\,(k\in\{1,...n\})} \theta\\
&\textstyle\sum_{k=1}^{n} \lambda_{kt}^r \mathbf{X}_{kt}^r \le \theta \mathbf{X}_{jt}^r\\
&\forall\, r: \boldsymbol{\lambda}_{kt}^r\left(y_{kt}^r - y_{jt}^r\right) \ge 0\\
&\textstyle\sum_{k=1}^{n} \lambda_{kt}^r = 1\\
&\forall\, r: \lambda_{kt}^r \ge 0\\
&\theta \ge 0.
\end{aligned}$$

The overall technical efficiency scores $TE_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right)$ of each DMU $j \in \{1, ..., n\}$ at period $t \in \{1, ..., T\}$ can be obtained in two ways: either once all the output-specific technical efficiency scores are computed with **(LP-1)**, by using the relationship established in (9), or in one step by the use of **(LP-2)**:

$$\begin{aligned}
&\mathrm{TE}_t\left(y_{jt}^1, ..., y_{jt}^s, \mathbf{X}_{jt}^1, ..., \mathbf{X}_{jt}^s\right) = \min_{\lambda_{kt}^r\,(r\in\{1,...s\},k\in\{1,...n\})} \eta\\
&\forall\, r: \textstyle\sum_{k=1}^{n} \lambda_{kt}^r \mathbf{X}_{kt}^r \le \eta \mathbf{X}_{jt}^r\\
&\forall\, k, \forall\, r: \boldsymbol{\lambda}_{kt}^r\left(y_{kt}^r - y_{jt}^r\right) \ge 0\\
&\forall\, r: \textstyle\sum_{k=1}^{n} \lambda_{kt}^r = 1\\
&\forall\, k, \forall\, r: \lambda_{kt}^r \ge 0\\
&\eta \ge 0.
\end{aligned}$$

2.4. Malmquist productivity index

The Malmquist productivity index (MPI) is used to compare $(y_{t+1}^1, ..., y_{t+1}^s, \mathbf{X}_{t+1}^1, ..., \mathbf{X}_{t+1}^s)$ and $(y_t^1, ..., y_t^s, \mathbf{X}_t^1, ..., \mathbf{X}_t^s)$. It is defined, as the geometric mean of the distance ratios taking period t and $t + 1$ as the year reference for the technology (as explained previously the subscript t and $t + 1$ on the distance functions and on the technical efficiency measurements refer to the year of the technology, i.e. the input requirement sets). In the rest of this section, we drop subscript j, referring to a specific DMU, for better readability.

$$\begin{aligned}
&\mathrm{MPI}(y_t^1, ..., y_t^s, y_{t+1}^1, ..., y_{t+1}^s, \mathbf{X}_t^1, ..., \mathbf{X}_t^s, \mathbf{X}_{t+1}^1, ..., \mathbf{X}_{t+1}^s) =\\
&= \left[\frac{D_t(y_{t+1}^1, \dots, y_{t+1}^s, \mathbf{X}_{t+1}^1, \dots, \mathbf{X}_{t+1}^s)}{D_t(y_t^1, \dots, y_t^s, \mathbf{X}_t^1, \dots, \mathbf{X}_t^s)} \times \frac{D_{t+1}(y_{t+1}^1, \dots, y_{t+1}^s, \mathbf{X}_{t+1}^1, \dots, \mathbf{X}_{t+1}^s)}{D_{t+1}(y_t^1, \dots, y_t^s, \mathbf{X}_t^1, \dots, \mathbf{X}_t^s)}\right]^{1/2}\\
&= \left[\left(\frac{TE_t(y_{t+1}^1, \dots, y_{t+1}^s, \mathbf{X}_{t+1}^1, \dots, \mathbf{X}_{t+1}^s)}{TE_t(y_t^1, \dots, y_t^s, \mathbf{X}_t^1, \dots, \mathbf{X}_t^s)} \times \frac{TE_{t+1}(y_{t+1}^1, \dots, y_{t+1}^s, \mathbf{X}_{t+1}^1, \dots, \mathbf{X}_{t+1}^s)}{TE_{t+1}(y_t^1, \dots, y_t^s, \mathbf{X}_t^1, \dots, \mathbf{X}_t^s)}\right)^{-1}\right]^{1/2}.
\end{aligned} \tag{10}$$

The benchmark value is 1. An index bigger than 1 implies a performance regress since, in that case, the inputs $\mathbf{X}_{t+1}^1, ..., \mathbf{X}_{t+1}^s$ are, on average, further from the efficient boundary than the inputs $\mathbf{X}_t^1, ..., \mathbf{X}_t^s$ for securing the corresponding outputs. An index smaller than 1 implies a performance progress. Indeed, in that case, the inputs $\mathbf{X}_t^1, ..., \mathbf{X}_t^s$ are further from the efficient boundary than are the inputs $\mathbf{X}_{t+1}^1, ..., \mathbf{X}_{t+1}^s$ for securing the corresponding outputs.

At this point, we remark that for settings with one output (i.e. $s = 1$), our index $MPI(y_t^1, ..., y_t^s, y_{t+1}^1, ..., y_{t+1}^s, \mathbf{X}_t^1, ..., \mathbf{X}_t^s, \mathbf{X}_{t+1}^1, ..., \mathbf{X}_{t+1}^s)$ coincides with the MPI of Caves et al. [1]. In settings with more than one output (i.e. $s > 1$), the two indexes are different since we consider that the inputs could be allocated to the outputs. As a result, our index has the advantages of increasing the realism and the discriminatory power of the performance analysis.

Attractively, the MPI could be decomposed into two components: efficiency change EC and technical change TC. The following decomposition is in line with the decomposition suggested by Färe et al. [3] for the MPI of Caves et al. [1]. In fact, when $s = 1$, our decomposition coincides with the Färe et al.'s [3] decomposition, while when $s > 1$ our decomposition offers the advantage of taking the links between inputs and outputs into account. These indexes are defined as follows:

$$\text{EC}(y_t^1,...,y_t^s,\, y_{t+1}^1,...,y_{t+1}^s,\, \mathbf{X}_t^1,...,\mathbf{X}_t^s,\, \mathbf{X}_{t+1}^1,...,\mathbf{X}_{t+1}^s)= \\ = \frac{D_{t+1}(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)}{D_t(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)} = \left(\frac{TE_{t+1}(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)}{TE_t(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)}\right)^{-1}. \tag{11}$$

$$\text{TC}(y_t^1,...,y_t^s,\, y_{t+1}^1,...,y_{t+1}^s,\, \mathbf{X}_t^1,...,\mathbf{X}_t^s,\, \mathbf{X}_{t+1}^1,...,\mathbf{X}_{t+1}^s)= \\ = \left[\frac{D_t(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)}{D_{t+1}(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)} \times \frac{D_t(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)}{D_{t+1}(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)}\right]^{1/2} \\ = \left[\left(\frac{TE_t(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)}{TE_{t+1}(y_{t+1}^1,\ldots,y_{t+1}^s,\mathbf{X}_{t+1}^1,\ldots,\mathbf{X}_{t+1}^s)} \times \frac{TE_t(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)}{TE_{t+1}(y_t^1,\ldots,y_t^s,\mathbf{X}_t^1,\ldots,\mathbf{X}_t^s)}\right)^{-1}\right]^{1/2}. \tag{12}$$

Efficiency change is interpreted as the change in how far observed inputs are from the minimum inputs needed to secure the output production between years t and $t+1$. Technical change captures the shift in technology between the two periods evaluated at t and $t+1$. The interpretation of these indexes is similar to the interpretation of the MPI. It means that an index smaller than 1 implies a technology/efficiency progress, while an index greater than 1 implies a technology/efficiency regress.

As such, the MPI could be rewritten exclusively as the product of the two previous indexes as follows:

$$\text{MPI}(y_t^1,...,y_t^s,\, y_{t+1}^1,...,y_{t+1}^s,\, \mathbf{X}_t^1,...,\mathbf{X}_t^s,\, \mathbf{X}_{t+1}^1,...,\mathbf{X}_{t+1}^s)= \\ = EC\,(y_t^1,...,y_t^s,\, y_{t+1}^1,...,y_{t+1}^s,\, \mathbf{X}_t^1,...,\mathbf{X}_t^s,\, \mathbf{X}_{t+1}^1,...,\mathbf{X}_{t+1}^s) \\ \times\, TC\,(y_t^1,...,y_t^s,\, y_{t+1}^1,...,y_{t+1}^s,\, \mathbf{X}_t^1,...,\mathbf{X}_t^s,\, \mathbf{X}_{t+1}^1,...,\mathbf{X}_{t+1}^s). \tag{13}$$

MPI and its decomposition into *EC* and *TC* cannot be computed directly because of their non-linear nature. However, it suffices to evaluate the linear program **(LP-2)** by taking t or $t+1$ as the reference year to obtain all the necessary technical efficiency scores to compute the *MPI* and its decomposition.

2.5. Output-specific Malmquist productivity indexes

Our output-specific modelling of the production process naturally allows us to define MPIs at the output level. In fact, it suffices to replace the overall distance function and technical efficiency measurement by the output-specific counterparts in definitions (10) to (13) to define those indexes. We obtain the following definitions:

$$\text{MPI}^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r) = \left[\frac{D_t^r(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{D_t^r(y_t^r,\mathbf{X}_t^r)} \times \frac{D_{t+1}^r(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{D_{t+1}^r(y_t^r,\mathbf{X}_t^r)}\right]^{1/2} \\ = \left[\left(\frac{TE_t^r(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{TE_t^r(y_t^r,\mathbf{X}_t^r)} \times \frac{TE_{t+1}^r(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{TE_{t+1}^r(y_t^r,\mathbf{X}_t^r)}\right)^{-1}\right]^{1/2}. \tag{14}$$

The decomposition into output-specific efficiency change and output-specific technical change is given by:

$$\text{MPI}^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r) = EC^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r) \\ \times\, TC^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r), \tag{15}$$

where the output-specific components of the decomposition are defined as:

$$\text{EC}^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r) = \frac{D_{t+1}^r(y_{t+1}^r,\, \mathbf{X}_{t+1}^r)}{D_t^r(y_t^r,\, \mathbf{X}_t^r)} = \left(\frac{TE_{t+1}^r(y_{t+1}^r,\, \mathbf{X}_{t+1}^r)}{TE_t^r(y_t^r,\, \mathbf{X}_t^r)}\right)^{-1}, \tag{16}$$

and

$$\text{TC}^r(y_t^r,\, y_{t+1}^r,\, \mathbf{X}_t^r,\, \mathbf{X}_{t+1}^r) = \left[\frac{D_t(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{D_{t+1}(y_{t+1}^r,\mathbf{X}_{t+1}^r)} \times \frac{D_t(y_t^r,\mathbf{X}_t^r)}{D_{t+1}(y_t^r,\mathbf{X}_t^r)}\right]^{1/2} \\ = \left[\left(\frac{TE_t(y_{t+1}^r,\mathbf{X}_{t+1}^r)}{TE_{t+1}(y_{t+1}^r,\mathbf{X}_{t+1}^r)} \times \frac{TE_t(y_t^r,\mathbf{X}_t^r)}{TE_{t+1}(y_t^r,\mathbf{X}_t^r)}\right)^{-1}\right]^{1/2}. \tag{17}$$

As for *MPI*, an output-specific index *MPI*^{r} greater than 1 implies a performance regress for output *r*, while an index smaller than 1 indicates a performance progress for output *r*. As such, the benchmark value is also 1. There is no straightforward relationship between the MPI and the output-specific MPIs, however, they are related by the link between the technical efficiency measurement and the output-specific technical efficiency measurements explained previously. The interpretation of the efficiency and technical changes for the output-specific level is also analogous to those for the aggregate level. Finally, to obtain the output-specific *MPI*^{r}'s and their decomposition in practice, it is enough to evaluate the linear programs **(LP-1)** by taking t or $t+1$ as the reference years for the technology.

As a final remark, we point out that, in general, it is better to use statistical tests to support the results found based on the overall and output-specific MPIs and their decomposition. Indeed, we should keep in mind that these results are descriptive, and thus lack of statistical foundations. See our application for an illustration of the use of (one- and two-sample) Kolmogorov-Smirnov tests to verify whether the distribution of the MPIs and their decomposition is smaller than one (reflecting an improvement), and whether one type of plant or electricity perform better than another type.

3. Application

Improving the performance of electricity plants is an important goal that both regulators and managers are trying to achieve. There are already several studies that measure the performances of the plants using nonparametric efficiency models. See, for example, Yaisawang and Klein [43]; Färe et al. [44]; Sarkis and Cordeiro [45]; Sueyoshi and Goto [46]; Cherchye et al. [35] for analyses of US electric utilities; Hattori [47] and Tone and Tsutsui [48]; Sueyoshi and Goto [49] for analyses of both Japanese and US electric utilities; Abbott [50] for an application for Australian electric utilities; Pacudan and de Guzman [51] for an application for the Philippines' electric utilities; Pombo and Taborda [52] for an application for Columbian electric utilities; Kulshreshtha and Parikh [53] for an application for Indian electric utilities; and Jamasb and Pollitt [54]; Korhonen and Luptacik [55]; and Giannakis et al. [56] for an analysis of European electric utilities.

In the US, there are different types of electricity generation plants that we can group into three main categories. Firstly, those that produce only one type of (renewable or non-renewable) electricity. Next, those that produce more than one type of (renewable or non-renewable) electricity. Finally, those that produce both renewable and non-renewable electricity. In this empirical application, we question the performance of the plants for renewable and non-renewable electricity generation. That is, we compare the three different types of plants and identify the best performing. In other words, we ask the following questions: Is it preferable to have single- or multi-electricity plants? Should plants focus on the production of renewable or non-renewable electricity or produce both? Once the best type of plant has been found in terms of performance, we also question the reasons for that better performance. We could point out two main causes that explain the performance differences between plants: efficiency and technical changes. Efficiency change reveals how the plants use their current technology to generate the electricity, while technical change shows how the plants have invested to innovate the production process.

Clearly, it is not obvious that the cause in the performance change is the same for each type of electricity production. As such, we cannot follow the modelling of the production process suggested by previous studies, since they regroup all types of electricity produced into a single output. On the contrary, we must split the electricity generation into two parts: renewable electricity (e.g. wind, solar, geothermal) and non-renewable electricity (e.g. coal, oil, gas). Another advantage of the modified setting is that it allows us to link the fuel input to non-renewable electricity production since this input is clearly not used to produce renewable electricity, as it is implicitly assumed in the previous studies.

To present our empirical application, we first present our data and discuss specificity of the set-up. Subsequently, we present our results and make use of statistical tests to support our conclusions.

3.1. Data and input and output section

We use data from the *eGRID* system that was developed by the Environmental Protection Agency (EPA) in the US. In particular, we use all the databases available between 2000 and 2012 (there are no database available after 2012). Unfortunately, the databases are not available for each year but seven exist for that period (2012, 2010, 2009, 2007, 2005, 2004, 2000). There are also databases before 2000, but to avoid a too small sample, we do not take those two additional databases into account.

A particular feature of the *eGRID* system is that, for every plant, it distinguishes between renewable (wind, solar, geothermal, hydro, and biomass) and non-renewable (coal, oil, gas, nuclear, and other fossil) electricity generation.[5] As such, we can split the plants into different categories: (1) *single-electricity plants*: plants that produce only one type of renewable or non-renewable electricity; (2) *multi-electricity plants*: plants that produce more than one type of renewable or non-renewable electricity; and (3) *mixed-electricity plants*: plant that produce both renewable and non-renewable electricity. While the output side of the electricity generation process is described in much detail by the *eGRID* system, the input side is not so detailed: only the fuel consumption is provided. A strategy, used, for example, by Tone and Tsutsui [65], Sarkis and Cordeiro [45]; Cherchye et al. [35]; and Walheer [37,38]; is to proxy the missing inputs (such as total assets, number of employees, etc.) by the nameplate capacity. We obtain the following setting: nameplate capacity (x^1) is used to produce non-renewable (y^1) and renewable (y^2) electricity. Fuel (x^2) is only used to generate non-renewable electricity. Adopting the notation of Section 2, for each plant j at period t we obtain:

$$\mathbf{Y}_{jt} = \begin{bmatrix} y_{jt}^1 \\ y_{jt}^2 \end{bmatrix},\ \mathbf{X}_{jt} = \begin{bmatrix} x_{jt}^1 \\ x_{jt}^2 \end{bmatrix},\ \mathbf{V}_{jt}^1 = \begin{bmatrix} 1 \\ 1 \end{bmatrix},\ \mathbf{V}_{jt}^2 = \begin{bmatrix} 1 \\ 0 \end{bmatrix},$$

$$\mathbf{X}_{jt}^1 = \mathbf{V}_{jt}^1 \odot \mathbf{X}_{jt} = \begin{bmatrix} x_{jt}^1 \\ x_{jt}^2 \end{bmatrix},\ \text{and}\ \mathbf{X}_{jt}^2 = \begin{bmatrix} x_{jt}^1 \\ 0 \end{bmatrix}.$$

3.2. Descriptive statistics

We start our presentation of the data by providing, in Table 1, the number of plants and the distribution per type of plant for the period. At this point, we remark that we concentrate our analysis on plants that have a positive electricity generation and that produce electricity for at least two periods (for the simple reasons that it is impossible to conduct an efficiency analysis for plants with no electricity generation, and that the MPIs require observation for two consecutive periods). An initial observation is that the numbers of plants in the US increases over the period (4648 in 2000–5929 in 2012). This pattern is not kept for every type of plant. Indeed, while the number of single-electricity plants has clearly increased; it is not the case for the multi-electricity plants. In fact, there is 1 multi-electricity plant for 2.46 single-electricity plants in 2000 and 1 multi-electricity plant for 4.81 single-electricity plants in 2012. Finally, the number of mixed-electricity plants is more or less stable for the period. At the electricity level, there is 1 renewable electricity generation plant for 1.38 non-renewable electricity generation plants in 2000; and 1 renewable electricity generation plant for 0.98 non-renewable electricity generation plants. This shows the increasing importance of renewable electricity in the US.

Table 1
Number of plants per type.

Year	Total	Multi-electricity plant		Mix	Single-electricity plant	
		Non-Renewable	Renewable	Mix	Non-Renewable	Renewable
2012	5929	957	3	353	1747	2869
2010	5364	1002	1	342	1656	2363
2009	5246	995	1	343	1659	2248
2007	5013	1058	1	335	1654	1965
2005	4839	1118	2	312	1566	1841
2004	4658	1109	1	316	1487	1745
2000	4648	1274	1	392	1215	1766

We continue our analysis by showing how the outputs and inputs are distributed between the types of plants. Table 2 presents those results. Total electricity generation has clearly increases over the period: around +10% for non-renewable electricity and +25% for renewable electricity. This confirms the increasing importance of renewable electricity for the US. Nevertheless, we remark that renewable electricity represents only around 12% of the total electricity production in 2012 (against around 10% in 2000). For non-renewable electricity, multi-electricity plants produce the highest proportion, but their importance decreases significantly for the period (71.82%–53.45%). For renewable electricity, it is the opposite, single-electricity plants are the most important plants with a stable production around 90% over the period. Finally, mixed-electricity plants represent only 2% of the generation of non-renewable electricity, and around 10% of the generation of renewable electricity. As such, the main role of those types of plants is to produce renewable electricity, while non-renewable electricity generation could be seen as a good by-product of the production process.

For the input side of the production process, there is a decrease of the fuel consumption (−6%), and a rise of nameplate capacity (+42%). This is rather intuitive as there are more and more plants in the US, explaining why overall inputs increase; but there are also more and more plants that produce renewable electricity, explaining why fuel input decreases slightly. Fuel is mostly used by the multi-electricity plants, but again, their share decreases. The same holds true for nameplate capacity and the numbers of boilers and generators.

All in all, this part reveals two important facts. One, there is a decreasing importance of multi-electricity plants; even if they still produce the largest share of non-renewable electricity. Two, there is an increasing importance of renewable electricity in the US, even if non-renewable electricity still represents the largest share of electricity generation in the US. Note that this is in line with recent policy implementations in the US that try to help the development of renewable electricity (for example, the Energy Policy Act of 2005, the Energy and Tax Extenders Act of 2008, the American Recovery and Reinvestment Act of 2009, and also renewable electricity production continues to be promoted by many states (as in 2007 when 25 states established renewable portfolio standards)). This argues for studying renewable and non-renewable electricity generation separately.

3.3. MPIs and decomposition

Using the linear programs **(LP-1)** and **(LP-2)**, we compute the output-specific and overall technical efficiency scores for the plants. Thanks to these scores, we calculate the MPIs and their decomposition into efficiency and technical changes, and the output-specific MPIs and their decomposition into output-specific efficiency and output-specific technical changes. We present the medians and averages when pooling all years together in Table 3. Detailed results per year are available in Tables 7, 8, and 9, available in the Appendix. We concentrate our

[5] Note that for the distinction between renewable and non-renewable electricity, we follow the *eGRID* system as in their database they distinguish between those two types of electricity.

Table 2
Inputs and outputs.

Year	Total	Multi-electricity plant			Single-electricity plant	
		Non-Renewable	Renewable	Mixed	Non-Renewable	Renewable
Non-Renewable electricity generation (MWh)						
2012	3552725742	53.45%	0.00%	2.06%	44.48%	0.00%
2010	3700392144	59.19%	0.00%	2.13%	38.68%	0.00%
2009	3535171562	58.65%	0.00%	1.70%	39.65%	0.00%
2007	3812874838	62.92%	0.00%	1.70%	35.38%	0.00%
2005	3703473450	65.53%	0.00%	1.79%	32.68%	0.00%
2004	3588054765	65.04%	0.00%	1.83%	33.13%	0.00%
2000	3462520527	70.20%	0.00%	2.12%	27.69%	0.00%
Renewable electricity generation (MWh)						
2012	494064231.7	0.00%	0.15%	8.91%	0.00%	90.94%
2010	428305376.7	0.00%	0.01%	9.98%	0.00%	90.01%
2009	419139977.2	0.00%	0.01%	10.01%	0.00%	89.98%
2007	352568486.7	0.00%	0.01%	12.42%	0.00%	87.57%
2005	357114088.7	0.00%	0.02%	11.66%	0.00%	88.32%
2004	351579558.4	0.00%	0.01%	12.38%	0.00%	87.61%
2000	355390790.4	0.00%	0.00%	14.26%	0.00%	85.74%
Fuel input (MMBtu)						
2012	26806591809	69.49%	0.00%	4.23%	25.51%	0.77%
2010	28339881054	76.31%	0.00%	4.23%	18.78%	0.68%
2009	26742618017	76.55%	0.00%	3.72%	19.07%	0.66%
2007	29763014512	79.96%	0.00%	3.11%	16.39%	0.53%
2005	29558610691	81.95%	0.00%	3.53%	13.95%	0.57%
2004	29946654205	79.73%	0.00%	3.68%	15.84%	0.74%
2000	29182201783	86.15%	0.00%	4.16%	9.36%	0.33%
Nameplate capacity (MW)						
2012	1150287.7	45.09%	0.03%	2.82%	39.08%	12.98%
2010	1119882.1	48.43%	0.00%	2.69%	37.50%	11.38%
2009	1104124.2	48.03%	0.00%	2.41%	38.58%	10.98%
2007	1063422.9	52.08%	0.00%	2.29%	36.06%	9.57%
2005	1044940.1	54.09%	0.00%	2.26%	34.55%	9.10%
2004	1021813.9	53.95%	0.00%	2.29%	34.83%	8.93%
2000	847180.8	62.45%	0.00%	2.96%	24.41%	10.18%

Table 3
Medians and averages for the period.

Index	All		Single		Multi		Mixed	
	Median	Average	Median	Average	Median	Average	Median	Average
MPI	1.02	1.03	1.02	1.01	0.98	0.99	1.03	1.05
EC	1.04	1.04	1.00	1.00	1.02	1.02	1.06	1.08
TC	1.00	0.99	1.01	1.01	0.97	0.97	1.02	1.01
MPI^1	0.99	1.00	1.02	1.03	0.98	0.99	1.03	1.04
EC^1	0.98	0.99	1.03	0.98	1.01	1.01	1.07	1.08
TC^1	1.03	1.02	1.02	1.03	0.96	0.97	1.00	1.01
MPI^2	1.01	1.02	0.99	1.00	–	–	1.04	1.03
EC^2	1.04	1.05	1.03	1.04	–	–	1.07	1.08
TC^2	0.98	0.99	0.97	0.98	–	–	1.01	1.02

discussion on the main results.

Let us start with the analysis of the MPI and its decomposition for the total electricity generation (MPI, EC and TC). On average, plants have faced a small performance regress for the total electricity generation. The average for the period is 1.03 (median of 1.02). This is mostly due to a negative efficiency change (average and median of 1.04), while the technical change is sometimes positive but not important enough to compensate (average of 0.99 and median of 1). This picture is clearly different when looking at single-, multi-, and mixed-electricity plants separately. Single-electricity plants present a status quo of their performance, confirmed by both the efficiency and technical change indexes. On the contrary, multi-electricity plants present, except in 2010–2009, an improvement in their performance. This improvement is mostly due to a positive technical change, indicating that important investment and innovation have occurred for this type of plant. Our descriptive statistics indicated previously the decrease of the number of multi-electricity plants in the US. The index results reveal that probably less well performing plants have disappeared, explaining the good performance that we observe. Finally, mixed-electricity plants have a regress of their performance for the period, and this holds true for both the efficiency and technical change index. This indicates that merging both renewable and non-renewable electricity generation into one plant does not improve the performance of the plants.

Next, we move to the analysis per type of electricity generation. For non-renewable electricity generation (MPI^1, EC^1, and TC^1), we see a performance progress, except in 2010–2009 and 2007–2005. This improvement is due mostly to a positive efficiency change. Again, when looking per type of plants, the pattern is clearly different. Single- and mixed-electricity plants present performance regress, while multi-electricity plants present performance progress. The regress is due to both efficiency and technical regress, while the progress is due to technical change progress. This is intuitive to find again this result as multi-output plants produce mostly non-renewable electricity (see our discussion of Table 2).

For renewable electricity (MPI^2, EC^2, and TC^2), we see that there is a performance regress. As such, the performance regress observed for the total electricity generation is mostly due to the production of this type of electricity. This also highlights the advantage of considering results for each type of electricity separately; it provides extra valuable information about the performances of the plants. The performance regress is mostly due to a negative efficiency change. Single-electricity plants have a status quo of their performance, but there is a positive technical change for these plants. This indicates that investment and innovation have been realized for single-electricity plants producing renewable electricity. In other words, it implies that single-electricity plants seem preferable for this type of electricity generation. Again, we do not see any economic reasons why mixed-electricity plants should be relied upon since the performances of these plants are rather poor. Finally, note that we do not present the results for the multi-electricity plants since, as discussed previously, those plants are mostly used to produce non-renewable electricity, and thus there is not enough multi-electricity plants producing renewable electricity to present any results.

3.4. Statistical tests

Our previous results are only descriptive; they are only based on averages and medians, and thus suffer from a lack of statistical foundation. To formally test our findings, we rely on one- and two-sample Kolmogorov-Smirnov tests (KS tests). The one-sample KS test is a nonparametric test that checks whether the distribution of one sample is consistent with a referent distribution, and the two-sample KS test is used to check whether the distributions of two samples are equal or not. In our context, we calibrate the test to check whether plants have better performance, i.e. a distribution smaller than 1, and to verify whether one type of plant has better performance than another type or whether one type of electricity over-performs the other; in other words, whether it has a distribution closer to 1. The $p-$values are available for the one-sample KS tests in Table 4 when pooling all years together, and per year in Tables 10, 11, and 12 in the Appendix. The $p-$values of the two-sample KS tests are available in Tables 5 and 6 when pooling all years, and per year in Tables 13 and 14 in the Appendix. In Table 4, we investigate whether there are differences for the indexes between the types of plants. In Table 5, we look for index differences between non-renewable and renewable electricity generation. We choose 0.05 for the size of the test.

Let us start with the $p-$values of the one-sample KS test. They confirmed that there is a performance regress (a p-value lager than 0.05 means that we reject the null hypothesis that the sample distribution is smaller than 1). Also, the $p-$values reveal that efficiency change is the main reason of the regress (i.e. larger $p-$values). Next, our previous observations for each type of plant are also confirmed by the $p-$values. Indeed, most of the $p-$values for the single- and mixed-electricity plants are larger than 0.05, while most are smaller than 0.05 for the multi-electricity plants. This confirms the better overall performances of multi-electricity plants. Also, it is confirmed that this is mainly due to the positive technical change ($p-$value is smaller than 0.05).

Table 4
One-sample KS $p-$values for the period.

Index	All	Single	Multi	Mixed
MPI	0.11	0.20	0.05	0.15
EC	0.16	0.08	0.16	0.34
TC	0.06	0.10	0.01	0.25
MPI^1	0.12	0.20	0.06	0.15
EC^1	0.05	0.07	0.09	0.19
TC^1	0.09	0.10	0.04	0.13
MPI^2	0.06	0.05	–	0.08
EC^2	0.13	0.13	–	0.08
TC^2	0.05	0.04	–	0.11

Table 5
Two-sample KS $p-$values for the period.

$MPI_1 > MPI_2$			$EC_1 > EC_2$			$TC_1 > TC_2$		
All	Single	Mixed	All	Single	Mixed	All	Single	Mixed
0.05	0.04	0.09	0.02	0.03	0.32	0.43	0.44	0.23

Table 6
Two-sample KS $p-$values for the period.

Single > Multi			Single > Mixed			Multi > Mixed		
MPI	MPI_1	MPI_2	MPI	MPI_1	MPI_2	MPI	MPI_1	MPI_2
0.31	0.31	–	0.04	0.06	0.04	0.04	0.03	–
EC	EC_1	EC_2	EC	EC_1	EC_2	EC	EC_1	EC_2
0.06	0.09	–	0.03	0.03	0.02	0.04	0.03	–
TC	TC_1	TC_2	TC	TC_1	TC_2	TC	TC_1	TC_2
0.38	0.37	–	0.10	0.14	0.02	0.03	0.04	–

At the electricity level, the performance progress for non-renewable electricity and the performance regress for renewable electricity are confirmed. Indeed, the $p-$values are, in general, smaller than 0.05 for the former, and larger for the latter. Next, the $p-$values indicate that multi-electricity plants have indeed the best performances for non-renewable due to better technical change indexes over time. Afterwards, for renewable electricity generation, we see that single-electricity plants have the best performances. Finally, technical change is positive for these plants.

Next, we analyze that the p-values of two-sample KS tests for non-renewable and renewable electricity. At a general level, we see that non-renewable electricity generation over-performs renewable, except in 2010–2009. This holds true for single-electricity plants, but not for mixed-electricity plants. This conclusion is clearly contrasted when looking at the $p-$values for efficiency change and technical change. While non-renewable electricity generation presents better efficiency change performances than renewable electricity generation, it is not the case for technical change performance. That is, the worst performances of renewable electricity are due to a not high enough technical change to compensate for negative efficiency change. This reveals that investment and innovation have been made for these plants, but they are not yet used in an efficient manner. We can expect that renewable electricity will present a better performance than non-renewable when this becomes the case. Finally, mixed-electricity plants do not present better performances for renewable electricity, although this represents their main production (see Table 2).

Finally, the $p-$values of two-sample KS tests when distinguishing between types of plants reveal that, at the overall level, multi-electricity plants present better performances than the two other types., and that single-electricity plants have better performances than mixed-electricity plants. This holds true only because multi-electricity plants over-perform for non-renewable electricity, but single-electricity plants are clearly the best for renewable electricity. The $p-$values for the efficiency and technical change confirm that overall single-electricity plants have higher efficiency changes, but smaller technical changes. The largest technical changes are those of multi-electricity plants. Nevertheless, single-electricity plants present good performances for technical change for renewable electricity.

4. Summary and discussion

We summarize our main findings in six points:

- The number of multi-electricity plants has decreased over the period, but they still produce more than 50% of non-renewable electricity. For renewable electricity, only single-electricity plants are important; they represent 90% of the production.
- Renewable electricity is increasing in importance in the US, even if non-renewable electricity still represents slightly less than 90% of total electricity generation.
- Overall, there is a regress of the performance for total electricity generation.
- Single-electricity plants have better performances for renewable electricity generation, but for non-renewable electricity, it is the multi-electricity plants that perform better.
- Mixed-electricity plants are only important for renewable electricity, but are outperformed by single-electricity plants. The same holds true for multi-electricity plants for non-renewable electricity.
- Overall, non-renewable electricity generation presents better performances than renewable electricity generation, but this is contrasted when looking at the efficiency and technical changes.

Finally, we point out some limitations for our empirical application. Firstly, data are not available for every year but only for seven years over the time span from 2000 to 2012. Next, as discussed in Section 3, although the output side of the electricity generation process is described in much detail by the *eGRID* system, the input side is not so detailed: only the fuel consumption is provided. As such, using nameplate capacity, although done in several previous studies, clearly represents an important limitation for our empirical application. Afterwards, in practice, plants also face environmental constraints. For example, they have to respect some greenhouse gas emission restrictions. This aspect is neglected in our study. Finally, other reasons could explain the performance differences. In our study, we focus our attention on economic reasons.

5. Conclusion

In this paper, we presented a new performance index and its decomposition for multi-output settings. The new index, which takes the form of a Malmquist productivity index (MPI), is specially designed for multi-output producers for several reasons. Firstly, the index takes the links between the inputs and the outputs into account. On the one hand, it accounts for inputs jointly used to produce all the outputs. These inputs give rise to economies of scope, which form a prime economic motivation to produce multiple outputs. On the other hand, it includes inputs allocated to specific output production processes. Next, the index provides results for each output individually. Clearly, it is not obvious that the causes in the performance changes are the same for each output in multi-output contexts. Finally, the index is nonparametric in nature, i.e. not based on any parametric/functional specification of the production technology. In multi-output contexts, it is very difficult to impose a specific production function and, importantly, this may have a huge impact on the results.

We proposed an application for the US electricity plants over the period 2000–2012. The results highlight that the aggregate performances of the plants have slightly decreased for the period considered, but this is mainly due to a negative performance change for renewable electricity production, while the performance of non-renewable electricity production is positive but not large enough to compensate. Our analysis also shows that the causes are completely different for each type of electricity. We found an efficiency progress and a technical regress for non-renewable electricity, and an efficiency regress and a technological progress for renewable electricity. Finally, we highlighted that multi-electricity plants are preferable for non-renewable electricity production, while single-electricity plants are the best in the production of renewable electricity.

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Appendix

Table 7
Results for total electricity generation

Year	All		Single		Multi		Mixed	
	Median	Average	Median	Average	Median	Average	Median	Average
Malmquist productivity index								
2012–2010	1.02	1.01	1.03	1.02	1.00	0.99	1.01	1.03
2010–2009	1.05	1.07	1.00	0.99	1.00	1.03	1.02	1.09
2009–2007	1.01	1.00	1.01	1.01	0.97	0.98	1.01	1.02
2007–2005	1.04	1.05	1.01	1.02	0.96	0.99	1.04	1.06
2005–2004	0.99	1.00	1.04	1.03	0.95	0.97	1.02	1.03
2004–2000	1.01	1.02	1.01	0.99	0.97	0.98	1.06	1.04
Efficiency change								
2012–2010	1.04	1.03	0.99	1.00	1.03	1.02	1.05	1.07
2010–2009	1.08	1.09	1.02	1.01	1.04	1.02	1.06	1.15
2009–2007	1.03	1.02	0.98	0.99	1.01	1.00	1.05	1.04
2007–2005	1.05	1.06	1.01	1.02	0.99	1.00	1.07	1.08
2005–2004	1.01	1.00	0.97	0.98	1.02	1.01	1.05	1.05
2004–2000	1.00	1.01	1.00	1.00	1.01	1.02	1.06	1.08
Technical change								
2012–2010	0.99	0.98	1.03	1.03	0.98	0.97	1.03	1.02
2010–2009	1.04	1.02	1.00	1.00	0.96	0.99	1.02	1.03
2009–2007	0.96	0.97	1.02	1.01	0.96	0.96	1.00	1.00
2007–2005	1.03	1.01	1.01	1.00	0.97	0.96	1.03	1.02

2005–2004	1.00	0.99	1.02	1.00	0.98	0.96	1.02	1.01
2004–2000	0.97	0.98	1.00	0.99	0.95	0.95	1.00	1.00

Table 8
Results for non-renewable electricity generation

Year	All		Single		Multi		Mixed	
	Median	Average	Median	Average	Median	Average	Median	Average
Malmquist productivity index								
2012–2010	0.98	1	1.03	1.04	1	0.99	1.02	1.03
2010–2009	1.05	1.07	1.07	1.08	1.01	1.03	1.07	1.08
2009–2007	0.99	0.99	0.99	1	0.97	0.98	1	1.02
2007–2005	1.01	1.02	1.02	1.03	0.98	0.99	1.04	1.05
2005–2004	0.97	0.97	1	1.01	0.96	0.96	1.02	1.03
2004–2000	0.98	0.99	1	1	0.97	0.98	1.05	1.04
Efficiency change								
2012–2010	0.96	0.99	1.04	1.01	1.01	0.98	1.05	1.07
2010–2009	1.02	1.01	1.06	1.03	1.04	0.99	1.1	1.15
2009–2007	0.95	0.99	0.98	0.98	1.01	1.00	1.03	1.04
2007–2005	0.97	1.01	1	0.99	0.99	1.00	1.06	1.08
2005–2004	0.98	1	1	0.97	0.99	1.01	1.06	1.05
2004–2000	0.96	0.98	0.96	0.97	1	1.02	1.07	1.08
Technical change								
2012–2010	1.00	1.02	1.05	1.06	0.96	0.97	1	1.02
2010–2009	1.07	1.08	1.08	1.09	0.98	0.99	1.01	1.03
2009–2007	1.00	1.01	0.99	1	1	0.97	0.99	1.00
2007–2005	1.02	1.01	1	1	0.95	0.96	1	1.02
2005–2004	1.03	1.04	1.01	1.05	0.97	0.96	1	1.01
2004–2000	1.02	1.03	1	1.04	0.94	0.95	1.01	1.00

Table 9
Results for renewable electricity generation

Year	All		Single		Multi		Mixed	
	Median	Average	Median	Average	Median	Average	Median	Average
Malmquist productivity index								
2012–2010	1.02	1.03	1.02	1.02	–	–	1.02	1.03
2010–2009	1.02	1.02	0.97	0.96	–	–	1.03	1.02
2009–2007	1	1.01	0.97	0.98	–	–	1.04	1.02
2007–2005	1.02	1.03	1	1.01	–	–	1.03	1.04
2005–2004	0.99	1.02	0.99	1.02	–	–	1.03	1.03
2004–2000	1.02	1.03	1	1	–	–	1.03	1.04
Efficiency change								
2012–2010	1.06	1.07	1.04	0.99	–	–	1.07	1.08
2010–2009	1.1	1.12	1.08	1.10	–	–	1.12	1.15
2009–2007	1.02	1.03	1.01	1.02	–	–	1.03	1.04
2007–2005	1.06	1.05	1.05	1.04	–	–	1.05	1.06
2005–2004	1.04	1.05	1.03	1.04	–	–	1.04	1.06
2004–2000	1.05	1.07	1.05	1.04	–	–	1.07	1.08
Technical change								
2012–2010	0.95	0.96	0.97	0.96	–	–	1	1.02
2010–2009	0.99	1.03	1	1.01	–	–	1.05	1.04
2009–2007	0.98	0.97	0.98	0.97	–	–	1.01	1.00
2007–2005	0.99	1	0.98	0.99	–	–	1.04	1.03
2005–2004	0.96	0.97	0.97	0.96	–	–	1.02	1.01
2004–2000	0.98	1	0.97	0.99	–	–	1.02	1.00

Table 10
One-sample KS $p-$values for total electricity generation

Year	All	Single	Multi	Mix
Malmquist productivity index				
2012–2010	0.12	0.12	0.04	0.12
2010–2009	0.16	0.04	0.13	0.09
2009–2007	0.12	0.15	0.03	0.06
2007–2005	0.09	0.32	0.06	0.32
2005–2004	0.06	0.26	0.02	0.27
2004–2000	0.08	0.28	0.04	0.03
Efficiency change				
2012–2010	0.23	0.05	0.13	0.42
2010–2009	0.35	0.07	0.23	0.38
2009–2007	0.10	0.04	0.16	0.28
2007–2005	0.18	0.19	0.18	0.38
2005–2004	0.05	0.05	0.17	0.32
2004–2000	0.07	0.06	0.10	0.27
Technical change				
2012–2010	0.05	0.14	0.01	0.23
2010–2009	0.12	0.08	0.02	0.34
2009–2007	0.01	0.04	0.01	0.28
2007–2005	0.06	0.16	0.01	0.29
2005–2004	0.05	0.13	0.01	0.18
2004–2000	0.04	0.06	0.00	0.18

Table 11
One-sample KS $p-$values for non-renewable electricity generation

Year	All	Single	Multi	Mix
Malmquist productivity index				
2012–2010	0.04	0.32	0.06	0.18
2010–2009	0.45	0.34	0.07	0.14
2009–2007	0.06	0.12	0.03	0.13
2007–2005	0.12	0.15	0.05	0.15
2005–2004	0.04	0.18	0.05	0.14
2004–2000	0.04	0.09	0.07	0.18
Efficiency change				
2012–2010	0.03	0.02	0.18	0.17
2010–2009	0.09	0.08	0.12	0.54
2009–2007	0.07	0.07	0.06	0.12
2007–2005	0.05	0.10	0.05	0.15
2005–2004	0.05	0.05	0.07	0.08
2004–2000	0.07	0.03	0.08	0.10
Technical change				
2012–2010	0.06	0.12	0.04	0.12
2010–2009	0.14	0.15	0.03	0.13
2009–2007	0.07	0.05	0.02	0.15
2007–2005	0.09	0.06	0.04	0.08
2005–2004	0.06	0.16	0.02	0.15
2004–2000	0.09	0.08	0.07	0.12

Table 12
One-sample KS $p-$values for renewable electricity generation

Year	All	Single	Multi	Mixed
Malmquist productivity index				
2012–2010	0.12	0.06	–	0.10
2010–2009	0.08	0.02	–	0.12
2009–2007	0.08	0.01	–	0.08

2007–2005	0.07	0.06	–	0.07
2005–2004	0.04	0.07	–	0.05
2004–2000	0.08	0.05	–	0.05
Efficiency change				
2012–2010	0.13	0.12	–	0.12
2010–2009	0.25	0.13	–	0.1
2009–2007	0.12	0.08	–	0.04
2007–2005	0.08	0.07	–	0.09
2005–2004	0.08	0.15	–	0.07
2004–2000	0.14	0.21	–	0.06
Technical change				
2012–2010	0.04	0.03	–	0.12
2010–2009	0.08	0.06	–	0.1
2009–2007	0.03	0.02	–	0.09
2007–2005	0.05	0.04	–	0.21
2005–2004	0.04	0.05	–	0.07
2004–2000	0.07	0.03	–	0.05

Table 13
Two-sample KS $p-$values per type of electricity

Year	$MPI_1 > MPI_2$			$EC_1 > EC_2$			$TC_1 > TC_2$		
	All	Single	Mixed	All	Single	Mixed	All	Single	Mixed
2012–2010	0.01	0.02	0.06	0.02	0.01	0.38	0.54	0.59	0.15
2010–2009	0.12	0.03	0.08	0.01	0.08	0.32	0.53	0.48	0.18
2009–2007	0.04	0.02	0.12	0.04	0.02	0.43	0.6	0.51	0.25
2007–2005	0.03	0.03	0.09	0.01	0.04	0.18	0.32	0.38	0.23
2005–2004	0.04	0.06	0.1	0.01	0.03	0.39	0.33	0.39	0.24
2004–2000	0.03	0.08	0.08	0.01	0.01	0.22	0.23	0.29	0.32

Table 14
Two-sample KS $p-$values per type of plant

Year	Single > Multi			Single > Mixed			Multi > Mixed		
MPI	MPI	MPI_1	MPI_2	MPI	MPI_1	MPI_2	MPI	MPI_1	MPI_2
2012–2010	0.45	0.44	–	0.02	0.12	0.01	0.01	0.02	–
2010–2009	0.08	0.09	–	0.03	0.08	0.05	0.03	0.04	–
2009–2007	0.32	0.31	–	0.01	0.03	0.05	0.02	0.01	–
2007–2005	0.43	0.42	–	0.05	0.05	0.07	0.04	0.04	–
2005–2004	0.32	0.33	–	0.07	0.03	0.02	0.06	0.05	–
2004–2000	0.28	0.27	–	0.04	0.02	0.01	0.03	0.03	–
EC	EC	EC_1	EC_2	EC	EC_1	EC_2	EC	EC_1	EC_2
2012–2010	0.02	0.15	–	0.03	0.04	0.03	0.02	0.04	–
2010–2009	0.05	0.17	–	0.05	0.02	0.01	0.04	0.05	–
2009–2007	0.04	0.02	–	0.04	0.01	0	0.05	0.03	–
2007–2005	0.12	0.17	–	0.02	0.03	0.03	0.08	0.01	–
2005–2004	0.07	0.01	–	0.01	0.02	0.01	0.02	0.04	–
2004–2000	0.05	0.02	–	0.05	0.03	0.05	0.02	0.03	–
TC	TC	TC_1	TC_2	TC	TC_1	TC_2	TC	TC_1	TC_2
2012–2010	0.34	0.38	–	0.12	0.32	0.02	0.01	0.02	–
2010–2009	0.32	0.33	–	0.05	0.4	0.01	0	0.02	–
2009–2007	0.31	0.29	–	0.02	0.06	0.03	0.02	0.04	–
2007–2005	0.28	0.31	–	0.01	0.02	0.04	0.02	0.03	–
2005–2004	0.45	0.42	–	0.23	0.01	0.01	0.04	0.05	–
2004–2000	0.56	0.51	–	0.14	0.02	0	0.02	0.07	–

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