Article

ENERGY & ENVIRONMENT

Energy–economy–environmental (3E) performance of Chinese regions based on the data envelopment analysis model with mixed assumptions on disposability

Energy & Environment
2018, Vol. 29(5) 664–684

DOI: 10.1177/0958305X18757057
journals.sagepub.com/home/eae
SAGE

Qingyou Yan[1,2], Xu Wang[1], Tomas Baležentis[3] and Dalia Streimikiene[3]

Abstract

This paper presents a modified environmental production technology which imposes the proper disposability on the undesirable outputs depending on the underlying technical properties. Then, aggregate and disaggregate (Russell-type) data envelopment analysis (DEA) models are proposed to evaluate the energy–economy–environment (3E) efficiency based on the modified technology (hereafter referred to as the 3E-DEA models). The non-radial Malmquist productivity index is adapted to model the changes in the 3E productivity over time. A case study of 3E efficiency analysis for the 30 Chinese administrative regions during 2011–2013 is presented. In general, Chinese regions did not perform well in terms of 3E goals as only three of them exhibited full efficiency. It was also found out that the eastern area showed the best 3E performance, whereas the central area followed suit, thus putting the western area at end of ranking. Still, some regions in the eastern area showed 3E efficiencies lower than those of some cities in the central and eastern areas. Anyway, most of the regions showed improving 3E productivity during 2011–2013.

[1]School of Economics and Management, North China Electric Power University, Beijing, China
[2]Beijing Key Laboratory of New Energy and Low-Carbon Development (North China Electric Power University), Changping, Beijing, 102206, China
[3]Lithuanian Institute of Agrarian Economics, Vilnius, Lithuania

Corresponding author:
Tomas Baležentis, Lithuanian Institute of Agrarian Economics, Kudirkos 18-2, Vilnius 03105, Lithuania.
Email: tomas@laei.lt

Keywords
Data envelopment analysis, undesirable outputs, strong and weak disposability, energy–economy–environmental efficiency, Malmquist index

Introduction

China has seen a great progress in the sense of economic development since the implementation of the policy of opening up in 1978. Indeed, the economic growth can be represented by an increase in the gross domestic product (GDP) from 364.52 billion Yuan in 1978 up to 67670.8 billion Yuan in 2015. However, economic growth does not necessarily imply economic development let alone sustainable development.[1] In the case of China, a remarkable economic growth is still coexistent with such problems as low-energy efficiency and serious environmental degradation.[2–4]

Currently, China is the largest energy-consuming country as well as the largest CO_2 emitter. As the production activity is usually a joint process where resource and non-resource inputs are used to produce desirable outputs along with undesirable ones. Under these circumstances, low-energy efficiency induces waste of energy resources and excessive emissions of pollutants. Amidst the increasing resource prices and concerns over the sustainable development, resource and environmental development strategies have been the two vital parts of strategies in the European Union, China, and many other nations.[5] Focusing on China, the aim to build a resource-saving and environment-friendly society has been raised here in the strategic documents. The gains in energy or environmental efficiency are indeed related to improvements in the total factor productivity (TFP).[6] Therefore, the measures of the TFP should be adjusted to account for energy and environmental efficiency.[7–9] However, if attention is paid to the aggregated energy and environmental efficiency without involving economic growth in the analysis, the long-term national development goals might be neglected, especially in the case of developing countries. The energy–economy–environmental (3E) concept (see e.g. Yi et al.[10]) offers a rationale for an integrated indicator, which comprises economic development, environmental protection, and energy utilization dimensions. Such a measure can provide the comprehensive information for the government of progress toward a sustainable economy. By identifying and implementing effective measures, the government can simultaneously encourage reduction in the energy inputs and alleviate the environmental pollution while maintaining the economic growth.

Methodologically, the 3E efficiency can be appraised by applying the frontier techniques relying on the theory of production economics. Among these techniques, data envelopment analysis (DEA) presented by Charnes et al.[11] is an appealing tool to evaluate the energy and environmental efficiencies of decision-making units (DMUs) as it allows imposing multiple desirable properties on the underlying technology and the measures of efficiency. Note that DEA is a nonparametric method and can easily accommodate multiple-inputs multiple-outputs settings by applying the linear programming.

A number of attempts have been made to incorporate environmental pressures into the analysis of efficiency and productivity. The studies on modeling the energy–environmental issues in the confines of the production theory can be divided into four groups.

In the first group, research ignored the undesirable outputs and only considered energy consumption as an input. Thus, the environmental efficiency was not taken into consideration. Ramanathan[12] employed DEA to compare the energy efficiency of alternate transportation modes. However, the shortcomings of this approach became apparent as ignoring the undesirable outputs, which are inevitable in most of production technologies did not allow to fully describe the performance of the DMUs.

In researches falling within the second group, the undesirable outputs started to be accounted for. Färe et al.[13] applied a hyperbolic measure to evaluate the efficiency with undesirable outputs. The latter approach, however, did not prevail due to its nonlinearity. Pittman,[14] Reinhard et al.,[15] and Hailu and Veeman[16] treated the undesirable outputs as the inputs in parametric and non-parametric frameworks focused on industrial and agricultural applications. Yet it is due to Färe and Grosskopf[17] that such a handling of undesirable outputs cannot reflect the real production process. Therefore, data transformation function to transform the undesirable outputs into "normal" outputs was put forward. Lovell et al.[18] transformed the values of undesirable outputs to their reciprocals. Seiford and Zhu[19] included the undesirable outputs into the DEA models after applying a monotone decreasing transformation on to them. In this way, the modified transformed variables work as a kind of desirable outputs when measuring the efficiency. Yeh et al.[20] applied this transformation when incorporating the undesirable outputs into analysis. Färe and Grosskopf[21] pointed out some drawbacks of the transformation-based approach and showed that it might produce awkward results; they also suggested another approach based on Färe et al.[13] to model the environmental technology. They proposed to impose the weak disposability on all the undesirable outputs to construct the environmental technology. Seiford and Zhu[22] responded to Färe and Grosskopf by pointing out that their directional distance function (DDF) is linked to the weighted additive model. The methods proposed by Färe and Grosskopf[21] have been generally accepted in the literature (however, Kuosmanen[23] offered a modified weak disposability technology). Zhou et al.[24] proposed the slacks-based efficiency measures to model the environmental efficiency based on the environmental technology. Zhou et al.[25] employed the non-radial DEA to measure the environmental efficiency with respect to the environmental technology. Zhou et al.[26] presented the different environmental DEA models under different returns-to-scale (RTS) assumptions and environmental technologies. Bi et al.[27] studied the effects on the energy efficiency from the environmental regulation with the slacks-based model. Note that Yang and Pollitt[28] pointed that there is a necessity to impose the proper disposability on the undesirable outputs depending on their technical features, which makes a significant difference to efficiency evaluation. From this viewpoint, it is inappropriate to impose the weak disposability on all the undesirable outputs.

Literature in the third group explicitly focuses on input use efficiency. As nonrenewable energy resources can be exhausted, the balance between economic growth and resource depletion needs to be maintained. Therefore, the inputs can be divided into energy and non-energy ones in efficiency and productivity analysis to reveal the trends in the energy efficiency. The utilization of energy resources can be improved by systematically applying such frameworks. Zhou and Ang[29] used the radial and non-radial DEA models to measure the energy efficiency of 21 Organization for Economic Co-operation and Development (OECD) countries by separating the energy inputs and the other ones. However, such an approach does not offer an integrated measure of energy and environmental efficiency.

As regards the fourth group, some integrated efficiency indicators encompassing both energy and environmental improvements have been presented. Bian and Yang[30] analyzed the energy–

environmental efficiency for the 30 Chinese provinces. They presented several DEA models and used Shannon's entropy when constructing the weights. Shi et al.[31] developed three DEA models under different assumptions regarding RTS to measure the energy–environmental efficiency in Chinese regional industries. Wang et al.[32] estimated the environmental efficiency, economic efficiency, economic–environmental efficiency, and two-stage efficiency for different provinces in China. Wang et al.[33] conducted the dynamic evaluation of energy and environmental efficiency through the window DEA. Iftikhar et al.[34] studied the energy and CO_2 emission efficiency in major economies by employing a slacks-based model. For a more detailed information about the development of DEA in energy–environmental areas, one can refer to the reviews by Zhou et al.,[35] Sahoo et al.,[36] and Zhou et al.[37]

In this study, we propose a 3E efficiency indicator to offer the decision makers' comprehensive information in regards to implementations of the goals of sustainable development. More specifically, this paper proposes both aggregate and disaggregate (Russell-type) non-radial 3E-DEA models. In order to facilitate dynamic analysis, we construct the Malmquist index based on the 3E-DEA, which identifies DMU performance over time. Indeed, the earlier literature[28,38,39] focused on aggregate measures and did not discuss the measures of the productivity change. The empirical analysis focuses on the 3E performance of the 30 Chinese provinces throughout 2011–2013.

The rest of the paper is organized as follows. Methodology section presents the modified technology considering where the undesirable outputs face different disposability assumptions depending on technical properties of their abatement, the aggregate and disaggregate (Russell-type) 3E-DEA models based on the modified technology, and the Malmquist 3E productivity index. Regional 3E efficiency analysis in China section presents the data sources and variables used for the empirical analysis and then employs the Russell-type 3E-DEA model to evaluate the Chinese regional 3E efficiency for the period 2011–2013. In addition, the Malmquist index is employed to analyze the developments in productivity across the provinces. Finally, conclusions are drawn in Conclusions section.

Methodology

The modified environmental DEA technology

Yang and Pollitt[28] argued that there is a need for assuming different disposability among undesirable and desirable outputs depending on the underlying technical characteristics. Later on, Chen et al.[39] proposed a generalizing model where the degree of abatement can be specified. In this paper, we follow the mixed disposability approach and offer some additional measures of efficiency and productivity change.

When modeling the economic activity, we suppose there are n independent homogenous DMUs, indexed over $j = 1, 2, \ldots, n$ and denoted as DMU_j. Each DMU consumes (possibly) multiple types of inputs to produce (possibly) multiple types of outputs. During the production process, both the desirable and undesirable outputs are dispensed. In addition, the inputs are categorized into energy inputs and non-energy inputs to consider the energy efficiency of each DMU. Here the vectors of energy inputs, non-energy inputs, desirable outputs, undesirable outputs are denoted by $X = (x_1, x_2, \ldots, x_m)$, $E = (e_1, e_2, \ldots, e_k)$, $Y(y_1, y_2, \ldots, y_s)$, and $U = (u_1, u_2, \ldots, u_t)$. The production process (production possibilities) can be described by means of technology set $T = \{(x, e, y, u) : (x, e) \text{ can produce } (y, u)\}$. T is assumed to a closed and bounded set, which guarantees that finite inputs can only produce finite outputs.

What is more, the energy inputs, non-energy inputs, and desirable outputs are assumed to be strongly disposable. In order to model the process with the desirable and undesirable outputs produced simultaneously, Färe et al.[13] imposed the following two assumptions on technology T:

1. Outputs are weakly disposable: if $0 \leq \theta \leq 1$ and $(x, e, y, u) \in T$, then $(x, e, \theta y, \theta u) \in T$. This implies that the proportional reduction in the desirable and undesirable outputs is possible.

2. Desirable and undesirable outputs are null-joint: if $(x, e, y, u) \in T$, $u = 0$, then $y = 0$. This implies that the only way to completely curb the generation of undesirable outputs is to halt the production.

Following this approach, the same assumption of weak disposability is applied with respect to each of the undesirable outputs, which might contradict the technical properties of the abatement technologies. Indeed, different undesirable outputs might have different abatement options. If one treats them equally, it might contradict the real situation. We can take the coal-fired power plants as an example. During the process of electricity generation there, both CO_2 and SO_2 are emitted. If people want to decrease the amount of them, the generation of the electricity would be decreased, which means the costs of electricity per kWh would be increased. As for CO_2, if 90% of its emission is decreased, the electricity generation might be reduced by 90% as well (depending on the direction of optimization). For this type of emissions, one can be imposed the weak disposability. Therefore, if one models CO_2 emission along with some other undesirable outputs with similar technical properties, weak disposability may be imposed on both of them. As for SO_2, the case would be different. It is possible to dispose of most of the SO_2 emission by using the desulphurization equipment with loss in the electricity generation of just several percents, which is inconsistent with the assumption of the weak disposability. Therefore, some undesirable outputs might not be suitable to be modeled under the assumption of the weak disposability; instead, the strong disposability should be imposed on them. All in all, the undesirable outputs might face different types of disposability depending on the associated technical properties. Considering these findings, the modified environmental DEA technology under the assumption of constant RTS can be given as:

$$
\begin{aligned}
T_R = \{(x, e, y, u) : \quad & \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, i = 1, \ldots, m; \\
& \sum_{j=1}^{n} \lambda_j e_{lj} \leq e_l, l = 1, \ldots, k; \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r, r = 1, \ldots, s; \\
& \sum_{j=1}^{n} \lambda_j u^w_{b_1 j} = u^w_{b_1}, b_1 = 1, \ldots, t_1; \\
& \sum_{j=1}^{n} \lambda_j u^s_{b_2 j} \leq u^s_{b_2}, b_2 = 1, \ldots, t_2\}
\end{aligned} \tag{1}
$$

where x_{ij} represents the ith non-energy input consumed by DMU_j, e_{lj} indicates the lth energy input consumed by DMU_j and y_{rj} stands for the rth desirable output produced by DMU_j.

The undesirable outputs are organized into the two groups according to the underlying technical properties of the associated abatement technologies. In this setting, $u^{w}_{b_1 j}$ represents the b_1th undesirable output associated with the weak disposability assumption produced by $\mathrm{DMU_j}$, whereas $u^{s}_{b_2 j}$ denotes the b_2th undesirable output associated with the strong disposability assumption. Note that $t_1 + t_2 = t$.

Based on the modified environmental DEA technology, we further propose the 3E-DEA models to measure the 3E efficiency and productivity change.

Aggregate 3E-DEA model

On the basis of the revised environmental DEA technology, we first present the aggregate 3E-DEA model. We term this model as the aggregate one as the input and output variables are scaled by different factors, yet these factors are not variable-specific. The aggregate model is formulated as follows:

$$
\begin{aligned}
&3EE_1 = \min \frac{k_1\varphi + k_2\varphi}{\eta} \\
&\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x^-} = x_{io}, i = 1, \ldots, m, \\
&\sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e^-} = \phi e_{lo}, l = 1, \ldots, k, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y^+} = \eta y_{ro}, r = 1, \ldots, s, \\
&\sum_{j=1}^{n} \lambda_j u^{w}_{b_1 j} = \varphi u^{w}_{b_1 o}, b_1 = 1, \ldots, t_1, \\
&\sum_{j=1}^{n} \lambda_j u^{s}_{b_2 j} + s_{b_2}^{u^-} = \varphi u^{s}_{b_2 o}, b_2 = 1, \ldots, t_2, \\
&0 < \phi \leq 1, \eta \geq 1, 0 < \varphi \leq 1, \\
&\lambda_j, s_i^{x^-}, s_l^{e^-}, s_r^{y^+}, s_{b_2}^{u^-} \geq 0
\end{aligned}
\tag{2}
$$

where subscript o indicates DMU_o is evaluated here, k_1 and k_2 are the two weights set a priori so that $k_1 + k_2 = 1$, $s_i^{x^-}$, $s_l^{e^-}$, $s_r^{y^+}$, and $s_{b_2}^{u^-}$ are the slack variables associated with the non-energy inputs, energy inputs, desirable outputs, and undesirable outputs, respectively, satisfying the strong disposability. It is clear that objective function of Model (2) seeks to proportionally decrease the energy inputs and undesirable outputs, and increase the desired outputs for a given amount of non-energy inputs. The DMU with a higher value in $3EE_1$ performs better in regards to the 3E approach if compared to the other DMUs. The index is a standardized one, so a DMU with $3EE_1 = 1$ is located on the production frontier and serves as a peer for the benchmarking. Note that the presence of the three coefficients in equation (2) allows for more flexibility in moving toward the production frontier: energy inputs, desirable outputs, and undesirable outputs are scaled independently.

Model (2) is a fractional programming problem. Therefore, one needs to transform it into a linear programming problem for the computational convenience. The linearized model is given as follows:

$$
\begin{aligned}
& 3EE_2 = \min k_1 l_1 + k_2 l_2 \\
& \text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x^-} = \beta x_{io}, i = 1, \ldots, m, \\
& \sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e^-} = l_1 e_{lo}, l = 1, \ldots, k, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y^+} = y_{ro}, r = 1, \ldots, s, \\
& \sum_{j=1}^{n} \lambda_j u_{b_1 j}^{w} = l_2 u_{b_1 o}^{w}, b_1 = 1, \ldots, t_1, \\
& \sum_{j=1}^{n} \lambda_j u_{b_2 j}^{s} + s_{b_2}^{u^-} = l_2 u_{b_2 o}^{s}, b_2 = 1, \ldots, t_2, \\
& 0 < \beta \leq 1, 0 < l_1 \leq 1, 0 < l_2 \leq 1, \\
& \lambda_j, s_i^{x^-}, s_l^{e^-}, s_r^{y^+}, s_{b_2}^{u^-} \geq 0
\end{aligned}
\tag{3}
$$

The equivalence between Models (2) and (3) can be established by dividing the two sides of each constraint in Model (2) by η and denoting $\frac{1}{\eta} = \beta$, $\phi\beta = l_1$, $\varphi\beta = l_2$, and $\lambda_j \beta = \lambda'_j$.

Besides an increased computational convenience, indicator $3EE_2$ is still restricted to fall within the interval bounded by zero and unity, which increases its interpretability. Therefore, the 3E efficiency can be analyzed by means of Model (3).

Definition 1. Let ϕ', φ' and η' be the optimal values of Model (2). If ϕ', φ' and η' are all equal to unity and all the slack variables are zero, the DMU is 3E-DEA efficient. Then, indicator $3EE_1$ equals unity.

However, there are some shortcomings pertinent to Models (2) and (3). Specifically, these models ignore the mix inefficiency while adjusting all the desirable outputs or energy inputs by the same proportion. This might mask certain potential improvement during the efficiency analysis. In addition, such an approach might reduce the discriminating power of the models and a number of DMUs might appear with 3EE equal to unity. This would make the ranking of the DMUs according to their 3E performance rather complicated. Therefore, we present the disaggregate Russell-type 3E-DEA model in the following subsection.

Russell-type 3E-DEA model

In order to account for inefficiencies arising due to input/output mix, we allow the scaling factors to vary across specific variables. By doing this, we arrive a

Russell-type measure.[7,40,41] The disaggregate Russell-type 3E-DEA model is then defined as follows:

$$3EE_3 = \min \frac{\sum_{l=1}^{k} k_l^1 \phi_l + \sum_{b_1=1}^{t_1} k_{b_1}^2 \varphi_{b_1} + \sum_{b_2=1}^{t_2} k_{b_2}^3 \tilde{\varphi}_{b_2}}{\sum_{r=1}^{s} k_r^4 \eta_r}$$

$$\begin{aligned}
&\text{s.t.} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^{x^-} = x_{io}, i = 1, \dots, m, \\
&\sum_{j=1}^{n} \lambda_j e_{lj} + s_l^{e^-} = \phi_l e_{lo}, l = 1, \dots, k, \\
&\sum_{j=1}^{n} \lambda_j y_{rj} - s_r^{y^+} = \eta_r y_{ro}, r = 1, \dots, s, \\
&\sum_{j=1}^{n} \lambda_j u_{b_1 j}^{w} = \varphi_{b_1} u_{b_1 o}^{w}, b_1 = 1, \dots, t_1, \\
&\sum_{j=1}^{n} \lambda_j u_{b_2 j}^{s} + s_{b_2}^{u^-} = \tilde{\varphi}_{b_2} u_{b_2 o}^{s}, b_2 = 1, \dots, t_2, \\
&0 < \phi_l \le 1, \eta_r \ge 1, 0 < \varphi_{b_1} \le 1, 0 < \tilde{\varphi}_{b_2} \le 1, \\
&\lambda_j, s_i^{x^-}, s_l^{e^-}, s_r^{y^+}, s_{b_2}^{u^-} \ge 0
\end{aligned} \tag{4}$$

The meaning of the notations here is basically the same as it is for Model (2). Here we have four kinds of user-specified weights to adjust the energy inputs, desirable outputs, and undesirable outputs. The constraints for the weights are $\sum_{l=1}^{k} k_l^1 + \sum_{b_1=1}^{t_1} k_{b_1}^2 + \sum_{b_2=1}^{t_2} k_{b_2}^3 = 1$ and $\sum_{r=1}^{s} k_r^4 = 1$. The index is also a standardized one, locating the efficiency scores in between zero and unity.

By altering the weights, the decision makers can adjust the importance of energy inputs, desirable outputs, and undesirable outputs in the construction of the 3E efficiency indicator. In this context, ϕ_l represents the relative propensity of a decision maker to limit the use of the lth energy input. The higher weights indicate that the decision makers want to reduce the use of a certain input to a higher extent. Similarly, η_r indicates the relative importance of increasing the rth desirable output from the viewpoint of the decision maker. Therefore, higher weights imply that the decision maker seeks to increase production in a certain output. Finally, φ_{b_1} and $\tilde{\varphi}_{b_2}$ imply the relative importance of curbing the undesirable outputs. Specifically, a higher weight associated with a certain undesirable output implies higher priority in reduction of a certain emission. The model is sensitive to whether the DMU increases the desirable outputs at the cost of the environmental pollution. Even if the DMU performs well in production of the desired outputs, low environmental performance would damper the 3E efficiency. Only DMUs operating in lines with the sustainable development approach can secure high levels of the 3E efficiency.

We can also obtain the dual (multiplier) form of Model (4) without the slack variables. For the details on transformation to the dual multiplier form, one can refer to Färe and Primont.[42] The dual model is defined as follows:

$$3EE_3 = \min\sum_{i=1}^{m} a_i x_{io}$$

$$\text{s.t.} \sum_{i=1}^{m} a_i x_{ij} + \sum_{l=1}^{k} d_l e_{lj} + \sum_{b_1=1}^{t_1} g_{b_1} u^{w}_{b_1 j} + \sum_{b_2=1}^{t_2} f_{b_2} u^{s}_{b_2 j} \geq \sum_{r=1}^{s} c_r y_{rj}, \tag{5}$$

$$k^1_l \geq d_l e_{lo}, k^2_{b_1} \geq g_{b_1} u^{w}_{b_1 o}, k^3_{b_2} \geq f_{b_2} u^{s}_{b_2 o}, k^4_r \leq c_r y_{ro},$$

$$a_i, d_l, g_{b_1}, f_{b_2}, c_r \geq 0$$

Here, we put some additive constraints on $\phi_l, \eta_r, \varphi_{b_1}$ and $\tilde{\varphi}_{b_2}$. Therefore, we force the inefficient DMUs to increase the desirable outputs, decrease the undesirable outputs and energy inputs when moving toward the production frontier. If we do not put the constraints on $\phi_l, \eta_r, \varphi_{b_1}$ and $\tilde{\varphi}_{b_2}$, the targets for the inefficient DMUs might be set by decreasing both the inputs and/or outputs. In other words, a DMU might decrease its undesirable outputs, energy inputs, and desirable outputs in order to become efficient, i.e. improve its 3E performance on the account of the desired outputs. With these constraints, the projection on the production frontier can be considered as a Pareto improvement.

By using the preset weights, we can specify the upper bounds of the linear combination of the energy inputs, the undesirable outputs faced by $\mathrm{DMU_o}$. The lower bound of the linear combination of the desired outputs can also be set in this manner. Compared to the output-oriented Charnes-Cooper-Rhodes model, the difference lies in that there are more constraints on the linear combinations of the inputs and outputs for $\mathrm{DMU_o}$. The dual (multiplier) model objective function also gives the lower bound of that for Model (4).

Again, Model (4) is a fractional programming problem. Therefore, we can transform it into an equivalent linear programming problem for computational convenience. As for the principles underlying the transformation into the equivalent linear programming problem, one can follow the logics outlined for Model (3).

Definition 2. Let ϕ'_l, η'_r, φ'_{b_1}, and $\tilde{\varphi}'_{b_2}$ be the optimal values of Model (4). If ϕ'_l, η'_r, φ'_{b_1}, and $\tilde{\phi}'_{b_2}$ are all equal to unity in Model (4), and all the slack variables are zero, then $\mathrm{DMU_o}$ is referred to as 3E-DEA efficient.

If ϕ'_l, η'_r, φ'_{b_1}, and $\tilde{\varphi}'_{b_2}$ all equal to unity, and all the slacks variables are zero, the energy inputs and undesirable outputs of the DMU cannot be decreased, and the desirable outputs cannot be increased. Hereby, the $3EE_3$ is unity and the DMU is 3E efficient.

If $\phi_1 = \cdots = \phi_k, \eta_1 = \cdots = \eta_s, \varphi_1 = \cdots = \varphi_{t_1}$ and $\tilde{\varphi}_1 = \cdots = \tilde{\varphi}_{t_2}$, Model (4) boils down to Model (2). Therefore, the objective value of Model (4) is smaller than that of Model (2), which can increase the discriminating power of Model (4). Besides these properties, another advantage of Model (4) is that it can adjust all the energy inputs, desirable outputs, and undesirable outputs by different proportions thereby adhering to the realistic economic or political considerations. Therefore, inefficient DMUs might be associated with more realistic targets.

Definition 3. Let $\varphi_l{}'$, $\eta_r{}'$, $\phi_{b_1}{}'$, $\tilde{\phi}_{b_2}{}'$, $s^{x-}_i{}'$, $s^{e-}_l{}'$, $s^{y+}_r{}'$, and $s^{u-}_{b_2}{}'$ be the optimal solutions of Model (5). Let $\widehat{x}_{io} = x_{io} - s^{x-}_i{}'$, $\widehat{e}_{lo} = \phi_l{}' e_{lo} - s^{e-}_l{}'$, $\widehat{y}_{ro} = \eta_r{}' y_{ro} + s^{y+}_r{}'$, $\widehat{u}_{b_1 o} = \varphi_{b_1}{}' u^{w}_{b_1 o}$, $\widehat{u}_{b_2 o} =$

$\tilde{\varphi}_{b_2}{}' u^s_{b_2 o} - s^{u-}_{b_2}{}'$, then $(\widehat{x}_{io}, \widehat{e}_{lo}, \widehat{y}_{ro}, \widehat{u}_{b_1 o}, \widehat{u}_{b_2 o})$ is called the projection point of $\mathrm{DMU_o}$ based on the modified environmental technology.

In order to prove that the projection point is 3E-DEA efficient, we introduce the following lemma.

Lemma 1. If $(x_{io}, e_{lo}, y_{ro}, u^w_{b_1 o}, u^s_{b_2 o})$ is the Pareto optimal solution of the multi-objective programming problem, $\mathrm{DMU_o}$ is 3E-DEA efficient.

Here, the multi-objective programming problem is

$$\begin{cases} \min\ F(X, E, Y, U^w_{b_1}, U^s_{b_2}) \\ s.t.\ (X, E, Y, U^w_{b_1}, U^s_{b_2}) \in T_R \end{cases}$$

In this formulation, $F(X, E, Y, U^w_{b_1}, U^s_{b_2}) = (X, E, -Y, U^w_{b_1}, U^s_{b_2})^T$.

Theorem 1. The projection point of $\mathrm{DMU_o}$ is 3E-DEA efficient.

Proof. Based on Definition 3, we have

$$\widehat{x}_{io} = \sum_{j=1}^{n} \lambda_j{}' x_{ij} \tag{6}$$

$$\widehat{e}_{lo} = \sum_{j=1}^{n} \lambda_j{}' e_{lj} \tag{7}$$

$$\widehat{y}_{ro} = \sum_{j=1}^{n} \lambda_j{}' y_{rj} \tag{8}$$

$$\widehat{u}^w_{b_1 o} = \sum_{j=1}^{n} \lambda_j{}' u^w_{b_1 j} \tag{9}$$

$$\widehat{u}^s_{b_2 o} = \sum_{j=1}^{n} \lambda_j{}' u^s_{b_2 j} \tag{10}$$

where $\lambda_j{}'$, $j = 1, 2, \cdots, n$, is the optimal solution of Model (4) when $(x_{io}, e_{lo}, y_{ro}, u^w_{b_1 o}, u^s_{b_2 o})$ is evaluated.

As for the first constraint of Model (5), we have the following equation based on the supplementary Karush-Kuhn-Tucker condition:

$$\lambda'_j \left(\sum_{i=1}^{m} a'_i x_{ij} + \sum_{l=1}^{k} d'_l e_{lj} + \sum_{b_1=1}^{t_1} g'_{b_1} u^w_{b_1 j} + \sum_{b_2=1}^{t_2} f'_{b_2} u^s_{b_2 j} - \sum_{r=1}^{s} c'_r y_{rj} \right) = 0, j = 1, 2, \ldots, n \tag{11}$$

where $(a'_i, d'_l, c'_r, g'_{b_1}, f'_{b_2})$ is the optimal solution of Model (5) when $(x_{io}, e_{lo}, y_{ro}, u^w_{b_1 o}, u^s_{b_2 o})$ is evaluated.

If we add the n equations in equation (11) together, we have

$$\sum_{i=1}^{m} d'_i \widehat{x}_{io} + \sum_{l=1}^{k} d'_l \widehat{e}_{lo} + \sum_{b_1=1}^{t_1} g'_{b_1} \widehat{u}^{w}_{b_1 o} + \sum_{b_2=1}^{t_2} f'_{b_2} \widehat{u}^{s}_{b_2 o} - \sum_{r=1}^{s} c'_r \widehat{y}_{ro} = 0 \tag{12}$$

Then, $\forall (x, e, y, u) \in T_R$, we have

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_i, i = 1, \ldots, m \tag{13}$$

$$\sum_{j=1}^{n} \lambda_j e_{lj} \leq e_l, l = 1, \ldots, k \tag{14}$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_r, r = 1, \ldots, s \tag{15}$$

$$\sum_{j=1}^{n} \lambda_j u_{bj} \leq u_b, b = 1, \ldots, t \tag{16}$$

Note that we do not make a distinction between the undesirable outputs following the strong disposability assumption and those following the weak disposability assumption here.

We also have

$$\sum_{i=1}^{m} d'_i x_{ij} + \sum_{l=1}^{k} d'_l e_{lj} + \sum_{b_1=1}^{t_1} g'_{b_1} u^{w}_{b_1 j} + \sum_{b_2=1}^{t_2} f'_{b_2} u^{s}_{b_2 j} - \sum_{r=1}^{s} c'_r y_{rj} \geq 0 \tag{17}$$

Then we can get

$$\begin{aligned}
&\sum_{i=1}^{m} d'_i x_i + \sum_{l=1}^{k} d'_l e_l + \sum_{b_1=1}^{t_1} g'_{b_1} u^{w}_{b_1} + \sum_{b_2=1}^{t_2} f'_{b_2} u^{s}_{b_2} - \sum_{r=1}^{s} c'_r y_r \\
&\quad \geq \sum_{i=1}^{m} d'_i \sum_{j=1}^{n} \lambda_j x_{ij} + \sum_{l=1}^{k} d'_l \sum_{j=1}^{n} \lambda_j e_{lj} + \sum_{b_1=1}^{t_1} g'_{b_1} \sum_{j=1}^{n} \lambda_j u^{w}_{b_1 j} + \sum_{b_2=1}^{t_2} f'_{b_2} \sum_{j=1}^{n} \lambda_j u^{s}_{b_2 j} - \sum_{r=1}^{s} c'_r \sum_{j=1}^{n} \lambda_j y_{rj} \\
&\quad = \sum_{j=1}^{n} \lambda_j \Big(\sum_{i=1}^{m} d'_i x_{ij} + \sum_{l=1}^{k} d'_l e_{lj} + \sum_{b_1=1}^{t_1} g'_{b_1} u^{w}_{b_1 j} + \sum_{b_2=1}^{t_2} f'_{b_2} u^{s}_{b_2 j} - \sum_{r=1}^{s} c'_r y_{rj} \Big) \\
&\quad = \sum_{i=1}^{m} d'_i \widehat{x}_{i0} + \sum_{l=1}^{k} d'_l \widehat{e}_{l0} + \sum_{b_1=1}^{t_1} g'_{b_1} \widehat{u}^{w}_{b_1 o} + \sum_{b_2=1}^{t_2} f'_{b_2} \widehat{u}^{s}_{b_2 o} - \sum_{r=1}^{s} c'_r \widehat{y}_{ro} \geq 0
\end{aligned} \tag{18}$$

If $(\widehat{x}_{io}, \widehat{e}_{lo}, \widehat{y}_{ro}, \widehat{u}^{w}_{b_1 o}, \widehat{u}^{s}_{b_2 o})$ is not the Pareto optimal solution of multi-objective programming, there exists $(x', e', y', u'^{w}_{b_1}, u'^{s}_{b_2}) \in T_R, x' \leq \widehat{x}, e' \leq \widehat{e}, y' \geq \widehat{y}, u'^{w}_{b_1} = \widehat{u}^{w}_{b_1}, u'^{s}_{b_2} \leq \widehat{u}^{s}_{b_2}$. Because $a'_i > 0, d'_l > 0, g'_{b_1} > 0, f'_{b_2} > 0, c'_r > 0$, we have

$$\begin{aligned} &\sum_{i=1}^{m} a'_i \widehat{x}_{io} + \sum_{l=1}^{k} d'_l \widehat{e}_{lo} + \sum_{b_1=1}^{t_1} g'_{b_1} \widehat{u}^{w}_{b_1 o} + \sum_{b_2=1}^{t_2} f'_{b_2} \widehat{u}^{s}_{b_2 o} - \sum_{r=1}^{s} c'_r \widehat{y}_{ro} > \\ &\quad \sum_{i=1}^{m} a'_i x'_i + \sum_{l=1}^{k} d'_l e'_l + \sum_{b_1=1}^{t_1} g'_{b_1} u'^{w}_{b_1} + \sum_{b_2=1}^{t_2} f'_{b_2} u'^{s}_{b_2} - \sum_{r=1}^{s} c'_r y'_r \end{aligned} \tag{19}$$

It is in contradiction with the previous proof. Therefore, $(\widehat{x}_{io}, \widehat{e}_{lo}, \widehat{y}_{ro}, \widehat{u}^{w}_{b_1 o}, \widehat{u}^{s}_{b_2 o})$ is the Pareto optimal solution of multi-objective programming. According to Lemma 1, $(\widehat{x}_{io}, \widehat{e}_{lo}, \widehat{y}_{ro}, \widehat{u}^{w}_{b_1 o}, \widehat{u}^{s}_{b_2 o})$ is 3E-DEA efficient.

Malmquist 3E productivity index

Model (4) can be used to evaluate the 3E efficiency of a certain DMU. If one is interested in the dynamics of the 3E performance of a certain DMU, Model (4) cannot offer proper information about it as different periods have different frontiers and peer DMUs. What is more, the sources of changes in productivity cannot be revealed. In order to tackle this problem, the Malmquist 3E productivity index can be constructed following Färe et al.[43]

Let τ and $\tau+1$ be the two consecutive time periods. The measurement of productivity involves both contemporaneous and mixed-period measures of inefficiency. Looking at observation from period τ, $3EE^{\tau}(x^{\tau}_o, e^{\tau}_o, y^{\tau}_o, u^{\tau}_o)$ and $3EE^{\tau+1}(x^{\tau}_o, e^{\tau}_o, y^{\tau}_o, u^{\tau}_o)$ are the 3E efficiency measures relative to the frontiers of periods τ and $\tau+1$, respectively. Similarly, the contemporaneous and mixed-period efficiencies for observation form period $\tau+1$ are defined as 3 $EE^{\tau+1}(x^{\tau+1}_o, e^{\tau+1}_o, y^{\tau+1}_o, u^{\tau+1}_o)$ and $3EE^{\tau}(x^{\tau+1}_o, e^{\tau+1}_o, y^{\tau+1}_o, u^{\tau+1}_o)$, respectively. We can then construct the Malmquist 3E productivity index for DMU_o $(M3EPI_o)$ as follows:

$$M3EPI_o = \left[\frac{3EPI^{\tau}(x^{\tau+1}_o, e^{\tau+1}_o, y^{\tau+1}_o, u^{\tau+1}_o)\, 3EPI^{\tau+1}(x^{\tau+1}_o, e^{\tau+1}_o, y^{\tau+1}_o, u^{\tau+1}_o)}{3EPI^{\tau}(x^{\tau}_o, e^{\tau}_o, y^{\tau}_o, u^{\tau}_o)\, 3EPI^{\tau+1}(x^{\tau}_o, e^{\tau}_o, y^{\tau}_o, u^{\tau}_o)}\right]^{1/2} \tag{20}$$

One can assess the change in 3E performance for DMU_o across the two different periods by considering the value of $M3EPI_o$: If $M3EPI_o$ is higher than unity, a DMU has improved in terms of the 3E performance. On the contrary, the values of $M3EPI_o$ below unity indicate that a DMU has deteriorated in this regard. Obviously, $M3EPI_o$ equal to unity indicates no change in productivity. The $M3EPI_o$ index can be decomposed into two parts to measure the contributions of the efficiency change (the first term) and the technological change (the second term):

$$M3EPI_o = \frac{3EPI^{m}(x^{m}_o, e^{m}_o, y^{m}_o, u^{m}_o)}{3EPI^{n}(x^{n}_o, e^{n}_o, y^{n}_o, u^{n}_o)} \times \left[\frac{3EPI^{n}(x^{m}_o, e^{m}_o, y^{m}_o, u^{m}_o)\, 3EPI^{n}(x^{n}_o, e^{n}_o, y^{n}_o, u^{n}_o)}{3EPI^{m}(x^{m}_o, e^{m}_o, y^{m}_o, u^{m}_o)\, 3EPI^{m}(x^{n}_o, e^{n}_o, y^{n}_o, u^{n}_o)}\right]^{1/2} \tag{21}$$

Regional 3E efficiency analysis in China

In this section, the Russell-type 3E-DEA model is employed to measure the 3E efficiency for the 30 regions in the mainland China for the years 2011–2013. We first present the data used and define the regions considered in the analysis. Then, we focus on the empirical results (efficiency and productivity change).

Data used

In order to model the production process, the labor force and capital stock are employed as the two non-energy inputs. Primary energy consumption is employed as the energy input. The GDP works as the only desirable output. As regards the undesirable outputs, we choose the emissions of CO_2, SO_2, and NO_X. Owing to the technical properties of the abatement technologies, the weak disposability is imposed on CO_2, whereas the strong disposability is imposed on SO_2 and NO_X.

The data on labor force, capital, primary energy consumption (including coal, oil, and natural gas), GDP, SO_2, and NO_X emissions are collected from China Statistical Yearbook, China Energy Statistical Yearbook and China Statistical Yearbook on Environment from 2011 to 2013. The capital stock is not directly available from the yearbook and, thus, was estimated by applying the perpetual inventory method. The long-run growth rates in investments (gross fixed capital formation) were approximated by using time series for 2000–2013. The procedure outlined by Liu et al.[44] was applied with province-specific rates of depreciation taken from Wu et al.[45] The amounts of CO_2 emissions are not available from the yearbooks, so we estimate it on the basis of data on fuel-mix following Liu et al.[46] Table 1 presents the descriptives for the input and output variables.

Description of the regions of China

The study covers the 30 regions of the mainland China with exception of Tibet due to the missing data. According to the geographical location, the 30 regions are categorized into three areas, namely the eastern, central, and western areas.

The eastern area includes three municipalities (Beijing, Tianjin, and Shanghai) and eight coastal provinces (Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan). It shows the fastest economic development among the three areas and GDP generated here comprises more than a half of the national GDP. This region has been attracting substantial amounts of foreign investments, which contribute to further economic development.

The central area covers 10 inland provinces (Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei, Hunan, and Guangxi). The economic development here is slower than that in the eastern area but still more robust than that in the western area. This includes two famous heavy industry bases (Heilongjiang and Jilin) and two key energy industry provinces (Inner Mongolia and Shanxi). Given its industrial structure, this area is energy-consuming emissions of waste gas due to its industry background.

The western area is made up of one municipality (Chongqing) and nine provinces (Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, and Tibet). This area has seen the lowest rates of economic growth among the three areas. However,

Table 1. Descriptive statistics for inputs and outputs.

Year		Labor force (million workers)	Capital stock (billion RMB)	Primary energy consumption (million tons of coal equivalent)	GDP (billion RMB)	CO_2 (million tons)	SO_2 (million tons)	NOx (million tons)
2011	Min	18.7	516.3	16.0	60.6	34.4	0.004	0.041
	Max	60.7	26,749.7	371.3	5321.0	870.1	1.827	1.801
	Mean	26.1	9865.6	140.8	1682.1	318.6	0.715	0.776
2012	Min	18.6	670.5	16.9	70.1	36.3	0.004	0.044
	Max	59.3	31,256.0	389.0	5706.8	913.3	1.749	1.761
	Mean	25.5	11,890.0	147.7	1859.8	327.7	0.683	0.754
2013	Min	18.4	876.0	17.2	81.6	36.7	0.004	0.044
	Max	59.1	36,789.1	35,358.0	6247.5	867.3	1.645	1.652
	Mean	25.3	14,214.2	142.5	2046.3	325.3	0.659	0.719

Table 2. Regional differences of inputs and outputs, average values for 2011–2013.

Area	Average labor force (million workers)	Average capital stock (billion RMB)	Average primary energy consumption (million tons of coal equivalent)	Average GDP (billion RMB)	Average CO_2 emissions (million tons)	Average SO_2 emission (million tons)	Average NOx emissions (million tons)
Eastern area	28.1	14,800.2	148.7	2050.1	328	0.866	0.78
Central area	26.2	11,800.1	140.2	1800.3	320	0.887	0.76
Western area	23.1	9600.3	136.3	1600.3	316	0.533	0.70

this area is endowed with natural resources and well-protected habitats. The average input and output values for the three areas are given in Table 2.

It can be seen that the labor force, capital stock, generation GDP, and CO_2 emissions concentrate in the eastern area. However, SO_2 and NO_X emission mainly concentrates in the central area due to the presence of heavy industry there. See, for instance, Cheng et al.[47] for discussion on differences in the industrial structure across the regions of China.

Results

We apply the 3E-DEA model to analyze the performance of the Chinese regions. Model (4) can be implemented once the weights of the Russell-type measure are imputed. In our case, the weights of the undesirable outputs and the energy inputs are set to 0.25, which indicates that the decision makers treat them equally important, i.e. reducing either of the undesirable outputs or the energy input is equally important. As there is a single desirable output in the model, the weight for GDP is set to unity. Table 3 shows the 3E efficiencies based on the Russell-type model for the 30 regions during 2011–2013.

In general, Chinese regions did not perform well in the sense of 3E efficiency. Indeed, Beijing, Shandong, and Hubei appeared as the only 3E-efficient regions. On average, the eastern area showed the highest average 3E efficiency if contrasted to the other areas. The second-highest average 3E efficiency was observed for the central area. However, there were some exceptions noticed. Even though Hubei and Hunan are located in the central area and

Table 3. 3E efficiencies for Chinese regions during 2011–2013.

Regions and areas		2011	2012	2013
Eastern area	Beijing	1	1	1
	Tianjin	0.482	0.513	0.507
	Hebei	0.288	0.271	0.203
	Liaoning	0.209	0.205	0.193
	Shanghai	0.255	0.252	0.237
	Jiangsu	0.355	0.362	0.363
	Zhejiang	0.280	0.290	0.290
	Fujian	0.337	0.281	0.238
	Shandong	1	1	1
	Guangdong	0.466	0.463	0.443
	Hainan	0.515	0.513	0.479
	Average	*0.471*	*0.468*	*0.450*
Central area	Shanxi	0.319	0.317	0.296
	Inner Mongolia	0.466	0.479	0.460
	Jilin	0.369	0.372	0.337
	Heilongjiang	0.363	0.378	0.376
	Anhui	0.278	0.274	0.265
	Jiangxi	0.337	0.345	0.361
	Henan	0.361	0.378	0.379
	Hubei	1	1	1
	Hunan	0.351	0.343	0.323
	Guangxi	0.465	0.452	0.428
	Average	*0.431*	*0.434*	*0.423*
Western area	Chongqing	0.307	0.332	0.338
	Sichuan	0.335	0.340	0.330
	Guizhou	0.223	0.204	0.188
	Yunnan	0.274	0.255	0.232
	Shaanxi	0.264	0.262	0.249
	Gansu	0.230	0.203	0.187
	Qinghai	0.255	0.259	0.250
	Ningxia	0.148	0.147	0.141
	Xinjiang	0.248	0.225	0.200
	Average	*0.253*	*0.247*	*0.235*
National average		*0.393*	*0.391*	*0.376*

Chongqing is located in the western area, their performance was better than that of Hebei which is located in the best-performing eastern area. These findings can be partially explained by the fact that pollution-intensive industries have been moved from Beijing to Hebei. Therefore, serious environmental problems in Hebei undermined its E3 efficiency in spite of high GDP generated there. Another interesting example is Sichuan located in the western area. The latter city showed better E3 performance than some cities in the central area. This implies Sichuan managed to simultaneously ensure the environmental protection and economic growth, which contributed to increase in the 3E efficiency. Ningxia that is located in the western area performed the worst in terms of the 3E efficiency among all the regions. Though Ningxia ensured protection of its environment quite well, sluggish slow economic development there negatively influenced the 3E efficiency. Therefore, the 3E

Table 4. 3E Malmquist index for Chinese regions, 2011–2013.

Regions and areas		2011–2012			2012–2013		
		M3EPI	EFFCH	TECH	M3EPI	EFFCH	TECH
Eastern area	Tianjin	1.161	1.065	1.09	1.14	0.989	1.153
	Hebei	1.165	0.94	1.239	0.934	0.749	1.247
	Liaoning	1.152	0.979	1.177	1.111	0.945	1.175
	Shanghai	1.265	0.985	1.284	1.298	0.942	1.377
	Jiangsu	1.351	1.02	1.324	1.364	1.003	1.36
	Zhejiang	1.323	1.038	1.275	1.292	1	1.292
	Fujian	0.974	0.833	1.17	1.058	0.849	1.247
	Guangdong	1.216	0.993	1.224	1.159	0.957	1.211
	Hainan	1.393	0.996	1.398	1.185	0.934	1.269
	Geometric mean	*1.216*	*0.981*	*1.239*	*1.164*	*0.926*	*1.257*
Central area	Shanxi	1.201	0.992	1.21	1.152	0.933	1.234
	Inner Mongolia	1.207	1.028	1.174	1.071	0.961	1.114
	Jilin	1.224	1.007	1.215	1.077	0.906	1.188
	Heilongjiang	1.262	1.043	1.21	1.361	0.993	1.37
	Anhui	1.228	0.987	1.245	1.211	0.966	1.254
	Jiangxi	1.298	1.022	1.27	1.429	1.047	1.365
	Henan	1.358	1.049	1.294	1.303	1.001	1.302
	Hunan	1.164	0.978	1.19	1.167	0.942	1.239
	Guangxi	1.091	0.97	1.124	1.075	0.949	1.134
	Geometric mean	*1.224*	*1.008*	*1.214*	*1.199*	*0.966*	*1.241*
Western area	Chongqing	1.368	1.079	1.267	1.407	1.02	1.38
	Sichuan	1.267	1.014	1.25	1.245	0.971	1.282
	Guizhou	1.147	0.916	1.253	1.228	0.921	1.334
	Yunnan	1.154	0.933	1.236	1.189	0.908	1.309
	Shaanxi	1.196	0.991	1.207	1.185	0.95	1.247
	Gansu	1.061	0.884	1.2	1.128	0.918	1.228
	Qinghai	1.261	1.017	1.24	1.222	0.964	1.268
	Ningxia	1.277	0.994	1.284	1.237	0.956	1.293
	Xinjiang	1.027	0.908	1.131	1.022	0.888	1.151
	Geometric mean	*1.191*	*0.969*	*1.229*	*1.203*	*0.943*	*1.275*
Geometric mean		*1.21*	*0.985*	*1.227*	*1.189*	*0.945*	*1.258*

efficiency indicator identified the best practice and the pathway for sustainable development at the regional level.

Next, we use the Malmquist 3E index to analyze the change in 3E productivity across the regions. Note that Beijing, Shandong, and Hubei are excluded from the analysis as they have always been on the production frontier. The results for the periods of 2011–2012 and 2012–2013 are presented in Table 4.

According to Table 4, a number of regions progressed in terms of the 3E productivity during 2011–2012 and 2012–2013. Looking at the period of 2011–2012, the technological change has contributed to the improvement in the 3E productivity of Chinese regions. Indeed, the same trend prevailed for 2012–2013. In order to identify the directions for improvement, we can focus on some specific regions. Hebei belongs to the eastern area and managed to improve its 3E productivity during 2011–2012. However, the 3E

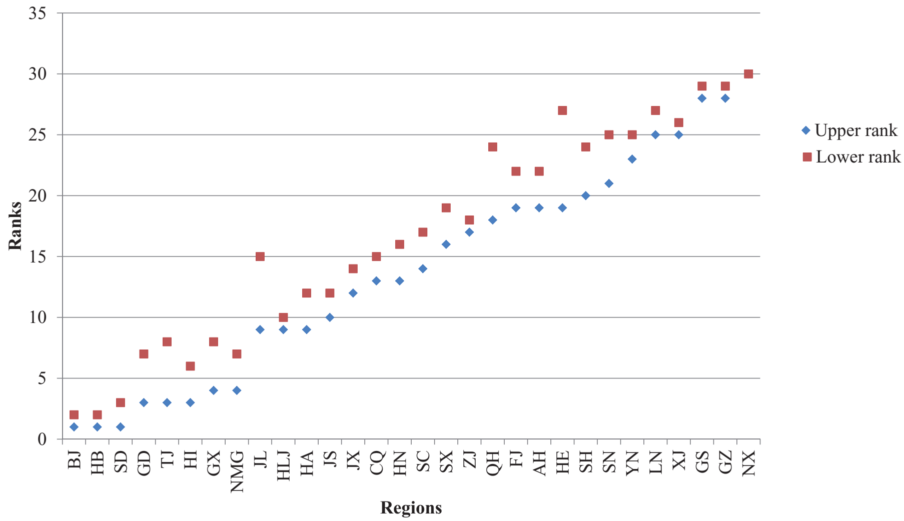

Figure 1. The differences in rankings of the regions due to changes in weights, 2013. *Note*: We use the first capital letters to denote the regions. For example, BJ stands for Beijing. As for the regions with the same letters, we make the following adjustments: HN represents Hunan, HI represents Hainan and HA represents Henan, HB stands for Hubei, HE stands for Hebei, SX stands for Shanxi, and SN stands for Shaanxi.

productivity decreased in the subsequent period of 2012–2013 due to unfavorable efficiency change. This might be related to increased environmental pressures due to establishment of factories and associated pollution here. All the eastern regions managed to improve their 3E during 2011–2013, which indicates the policies carried out by the local governments conformed to the rules of sustainable development. Note that this region had seen an economic expansion without serious environmental considerations before, yet the present results imply this trend has been reversed. Therefore, further development corresponds to the concept of 3E and might render increase in the well-being of the population. All the regions in the western area also improved 3E productivity during 2011–2013. This region is specific with slower economic growth, yet the environmental pressures have been properly managed as evidenced by the increase in 3E productivity.

The 3E-DEA models presented in this paper require the choice of the weights for input and output variables. As it was mentioned before, we set equal weights to inputs and undesirable outputs (i.e., 0.25). We further conduct the sensitivity analysis for Model (4). Specifically, we define the low-, middle-, and high-importance weights for undesirable outputs and energy inputs as 0.1, 0.25, and 0.4, respectively. If the weight for one of the variables is determined, the remaining weights are allocated uniformly to add up to unity. Thus, the nine patterns of weights are established. The results of the sensitivity analysis are presented in Figure 1.

The dotted line demonstrates the gaps between the highest and lowest ranks of the regions due to changes in the weights. It is clear that the changes are quantitative ones rather than qualitative ones. This indicates the 3E-DEA model is not sensitive to perturbations in weights of the variables. The highly-ranked regions such as Beijing, Shandong, and Hubei showed little variation in ranks. Note that most of these regions are located in the east of China. The variation is also limited for the worst-performing regions (e.g., Ningxia).

The highest spread is observed for regions with average or higher 3E performance. For example, if CO_2 is given a higher weight, Jilin ranks 15th among the 30 regions. If CO_2 is given a lower weight, Jilin ascends and ranks 11th among the 30 regions.

Conclusions

This paper proposed the 3E performance indicators and the associated productivity index. These techniques allow assessing performance in regards to the goals of sustainability. The key contribution of this paper lies in that the modified environmental technology has been presented to impose the appropriate disposability assumptions on different undesirable outputs. The aggregate 3E-DEA model and the equivalent linear programming problems for computational convenience were presented. The aggregate model ignores the mix effects and its discriminating power is not very high. Therefore, the Russell-type 3E-DEA model was also presented. The non-radial Malmquist 3E productivity index was constructed to model the changes in the 3E performance over time.

The Russell-type 3E-DEA model was employed to evaluate the 3E performance of 30 regions of China during 2011–2013. The results indicate that most of the regions did not perform well in the sense of 3E goals. On average, the eastern area performed better than the other two areas. However, certain cities constitute exceptions to this pattern. The Malmquist show the trends and sources of changes in the 3E productivity over the time. Almost all the regions showed improving 3E productivity for 2011–2013 as suggested by the Malmquist index. Technological change appeared as the key factor driving the increase in 3E productivity. This indicates that shifts in industrial structure, gains in energy efficiency, and abandoning of the backward capacity successfully pushed the production frontier away.

Sample and area averages indicated that efficiency change was negative in general. This implies that most of the provinces did not manage to improve their productivity to the same extent as the frontier provinces did. The lowest value of the latter variable was observed in the eastern area and, particularly, in Hebei province. Analysis of the efficiency change terms can provide a basis for allocating support for innovations which could ensure a more intensive spillover of novel technologies in order to reduce the gaps in productivity.

The sensitivity analysis was also implemented to check whether perturbations in weighting of the variables affect the ranking of the regions. The results indicate the Russell-type 3E-DEA model is not sensitive to changes in the weights.

The model can be applied to assess the development in the sense of the 3E objectives. Suchlike analysis can be iterated in different countries in order to assess the effectiveness of sustainable development policies there.

Acknowledgements

This work is supported by the Research Base Project of Beijing Social Science Foundation of China Grant No. 16JDGLB023.

Declaration of conflicting interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) disclosed receipt of the following financial support for the research, authorship, and/or publication of this article: This research is funded by the European Social Fund according to the activity "Improvement of researchers' qualification by implementing world-class R&D projects" of Measure No. 09.3.3-LMT-K-712.

ORCID iD

Tomas Baležentis http://orcid.org/0000-0002-3906-1711
Dalia Streimikiene http://orcid.org/0000-0002-3247-9912

References

1. Fuinhas JA, Marques AC, Almeida P, et al. Two centuries of economic growth: international evidence on deepness and steepness. *Transf Bus Econ* 2016; 15: 192–206.
2. Li Y and Oberheitman A. Challenges of rapid economic growth in China: reconciling sustainable energy use, environmental stewardship and social development. *Energ Policy* 2009; 34: 1412–1422.
3. Zhao QR, Chen QH, Xiao YT, et al. Saving forests through development? Fuelwood consumption and the energy-ladder hypothesis in rural southern China. *Transf Bus Econ* 2017; 16:199–219.
4. Song ML and Wang SH. Market competition, green technology progress and comparative advantages in China. *Manage Decis* 2018; 56: 188–203.
5. Ang BW. Monitoring changes in economy-wide energy efficiency: from energy-GDP ratio to composite efficiency index. *Energ Policy* 2006; 34: 578–582.
6. Boyd GA and Pang JX. Estimating the linkage between energy efficiency and productivity. *Energ Policy* 2000; 28: 289–296.
7. Wang K and Wei YM. Sources of energy productivity change in China during 1997-2012: a decomposition analysis based on the Luenberger productivity indicator. *Energ Econ* 2016; 54: 50–59.
8. Feng C, Wang M, Liu GC, et al. Green development performance and its influencing factors: a global perspective. *J Clean Prod* 2017; 144: 323–333.
9. Song ML, Peng J, Wang JL, et al. Better resource management: an improved resource and environmental efficiency evaluation approach that considers undesirable outputs. *Resour Conserv Recy* 2018; 128: 197–205.
10. Yi Q, Feng J, Wu YL, et al. 3E (energy, environmental, and economy) evaluation and assessment to an innovative dual-gas polygeneration system. *Energy* 2014; 66: 285–294.
11. Charnes A, Cooper WW and Rhodes E. Measuring the efficiency of decision making units. *Eur J Oper Res* 1978; 2: 429–444.
12. Ramanathan R. A holistic approach to compare energy efficiencies of different transport models. *Energ Policy* 2000; 28: 743–747.
13. Färe R, Grosskopf S, Lovell CAK, et al. Multilateral productivity comparisons when some outputs are undesirable: a nonparametric approach. *Rev Econ Stat* 1989; 71: 90–98.
14. Pittman RW. Issue in pollution control: interplant cost differences and economies of scale. *Land Econ* 1981; 57: 1–17.
15. Reinhard S, Lovell CAK and Thijssen G. Environmental efficiency with multiple environmentally detrimental variables; estimated with SFA and DEA. *Eur J Oper Res* 2000; 121: 287–303.
16. Hailu A and Veeman TS. Non-parametric productivity analysis with undesirable outputs: an application to the Canadian pulp and paper industry. *Am J Agr Econ* 2001; 83: 605–616.
17. Färe R and Grosskopf S. Non-parametric productivity analysis with undesirable outputs: comment. *Am J Agr Econ* 2003; 85: 1070–1074.
18. Lovell CAK, Pastor JT and Turner JA. Measuring macroeconomic performance in the OECD: a comparison of European and non-European countries. *Eur J Oper Res* 1995; 87: 507–518.

19. Seiford LM and Zhu J. Modeling undesirable factors in efficiency evaluation. *Eur J Oper Res* 2002; 142: 16–20.
20. Yeh TL, Chen TY and Lai PY. A comparative study of energy utilization efficiency between Taiwan and China. *Energ Policy* 2010; 38: 2386–2394.
21. Färe R and Grosskopf S. Modeling undesirable factors in efficiency evaluation: comment. *Eur J Oper Res* 2004; 157: 242–245.
22. Seiford LM and Zhu J. A response to comments on modeling undesirable factors in efficiency evaluation. *Eur J Oper Res* 2005; 161: 579–581.
23. Kuosmanen T. Weak disposability in nonparametric production analysis with undesirable outputs. *Am J Agr Econ* 2005; 87: 1077–1082.
24. Zhou P, Ang BW and Poh KL. Slacks-based efficiency measures for modeling environmental performance. *Ecol Econ* 2006; 60: 111–118.
25. Zhou P, Poh KL and Ang BW. A non-radial DEA approach to measuring environmental performance. *Eur J Oper Res* 2007; 178: 1–9.
26. Zhou P, Ang BW and Poh KL. A survey of data envelopment analysis in energy and environment studies. *Eur J Oper Res* 2008; 189: 1–18.
27. Bi GB, Song W, Zhou P, et al. Does environmental regulation affect energy efficiency in China's thermal power generation? Empirical evidence from a slacks-based DEA model. *Energ Policy* 2014; 66: 537–546.
28. Yang HL and Pollitt M. The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: environmental performance of Chinese coal-fired power plants. *Energ Policy* 2010; 38: 4440–4444.
29. Zhou P and Ang BW. Linear programming models for measuring economy-wide energy efficiency performance. *Energ Policy* 2008; 36: 2911–2916.
30. Bian Y and Yang F. Resource and environment efficiency analysis of provinces in China: a DEA approach based on Shannon's entropy. *Energ Policy* 2010; 38: 1909–1917.
31. Shi G, Bi J and Wang J. Chinese regional industrial energy efficiency evaluation based on a DEA model of fixing non-energy inputs. *Energ Policy* 2010; 38: 6172–6179.
32. Wang Q, Zhou P and Zhou D. Efficiency measurement with carbon dioxide emissions: the case of China. *Appl Energ* 2012; 90: 161–166.
33. Wang K, Yu S and Zhang W. China's regional energy and environmental efficiency: a DEA window analysis based dynamic evaluation. *Math Comput Model* 2013; 58: 1117–1127.
34. Iftikhar Y, He WJ and Wang ZH. Energy and Co_2 emissions efficiency of major economies: a nonparametric analysis. *J Clean Prod* 2016; 139: 779–787.
35. Zhou P, Ang BW and Poh KL. Measuring environmental performance under different environmental DEA technologies. *Energ Econ* 2008; 30: 1–14.
36. Sahoo BK, Luptacik M and Mahlberg B. Alternative measures of environmental technology structure in DEA: an application. *Eur J Oper Res* 2011; 215: 750–762.
37. Zhou HB, Yang Y, Chen Y, et al. Data envelopment analysis application in sustainability: the origins, development and future directions. *Eur J Oper Res* 2018; 264: 1–16.
38. Roshdi I, Hasannasab M ,Margaritis F, et al. Generalised weak disposability and efficiency measurement in environmental technologies. *Eur J Oper Res* 2018; 266: 1000–1012.
39. Chen L, Wang Y-M and Lai FJ. Semi-disposability of undesirable outputs in data envelopment analysis for environmental assessments. *Eur J Oper Res* 2017; 260: 655–664.
40. Pastor JT, Ruiz JL and Sirvent I. An enhanced DEA Russell graph efficiency measure. *Eur J Oper Res* 1999; 115: 596–607.
41. Fukuyama H and Weber WL. A directional slacks-based measure of technical inefficiency. *Socio-Econ Plan Sci* 2009; 43: 274–287.
42. Färe R and Primont D. *Multi-output production and duality: theory and applications*. New York: Springer Science+Business Media, 1995.

43. Färe R, Grosskopf S and Roos P. *Malmquist productivity indexes: a survey of theory and practice*. New York: Springer Science+Business Media, 1998.
44. Liu GT, Wang B and Zhang B. A coin has two sides: which one is driving China's green TFP growth? *Econ Syst* 2016; 40: 481–498.
45. Wu JD, Li N and Shi PJ. Benchmark wealth capital stock estimations across China's 344 prefectures: 1978 to 2012. *China Econ Rev* 2014; 31: 288–302.
46. Liu LC, Wang NJ, Wu G, et al. China's regional carbon emissions change over 1997-2007. *Int J Energ Environ* 2010; 1: 161–176.
47. Cheng ZH, Li LS and Liu J. Industrial structure, technical progress and carbon intensity in China's provinces. *Renew Sust Energ Rev* 2018; 81: 2935–2946.

Qingyou Yan is with North China Electric Power University. Prof. Yan is also a vice-director of the MBA School at North China Electric Power University. His research areas include energy policy, quantitative analysis of energy systems and optimization.

Xu Wang is a graduate student at North China Electric Power University. His research areas include operational research, quantitative analysis of energy systems and optimization.

Tomas Baležentis is a Principal Researcher and the Head of the Department at Lithuanian Institute of Agrarian Economics. He holds PhD degrees from Vilnius University, Lithuania, and University of Copenhagen, Denmark. Dr Balezentis has published articles on multi-criteria decision making, efficiency analysis and agricultural economics in such outlets as Agricultural Economics, European Journal of Operational Research, Applied Energy, and Journal of Productivity Analysis.

Dalia Streimikiene is a Principal Researcher at Lithuanian Institute of Agrarian Economics. Her research interests include sustainable development, energy economics and resource economics.