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Measuring and Analyzing Operational Efficiency and Returns to Scale in a Time Horizon: Assessment of China's Electricity Generation & Transmission at Provincial Levels

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Abstract: This study discusses the assessment of OE (operational efficiency) and RTS (returns to scale) over a time horizon. Many previous DEA (Data Envelopment Analysis) studies have discussed how to measure OE/RTS. However, their works did not consider the measurement over time. The important feature of the proposed approach is that our models are different from standard ones in terms of factor (inputs and outputs) unification. A problem with standard models is that they produce different efficiency measures for input and output orientations. Consequently, they yield different OE and RTS estimates depending upon which production factor is used for measurement. To handle the difficulty, we develop a new DEA formulation whose efficiency measure is determined after combining inputs and outputs, and then we discuss how to measure the types of RTS. The other methodological feature is that the proposed model incorporates a time horizon. As an empirical application, this study considers electricity generation and transmission across Chinese provinces from 2006 to 2019. The first key outcome is that the performance of China's electricity generation and transmission system tends to improve with an annual growth rate of 0.45% across time. The second outcome is that, during the observed periods, China has more occurrences of decreasing rather than increasing RTS. As an implication, some provinces (e.g., Jiangxi and Hainan) need to increase their generation sizes to enhance their OE measures, while other provinces (e.g., Jiangsu and Zhejiang) should decrease their generation sizes. Finally, this study confirms significant technological heterogeneity across Chinese provinces and groups.

Keywords: data envelopment analysis; returns to scale; operational efficiency; electricity generation and transmission

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1. Introduction

In performance assessment, the DEA (data envelopment analysis) has gained a great academic reputation. The DEA, first proposed by Charnes et al. [1], has wide applications in the research of performance evaluation. The approach has been widely applied to assess energy sectors, often power sectors. According to a recent literature survey by Sueyoshi and Goto [2], the DEA has several methodological merits because it is a non-parametric approach (i.e., measuring weights, not parameters, among factors), and it has a high level of computational tractability (i.e., solving by linear programming). In addition, DEA is very useful in providing various technology-based measures (e.g., returns to scale). These unique features provide us with useful and important business and policy information about production technology.

In this study, we discuss how to determine the degree of OE (operational efficiency) and how to examine the economic concept of RTS (returns to scale) over a time horizon. The RTS originally implied how much an output could increase due to a one-unit increase in an input. We determine the degree of RTS by comparing a proportional output increase with the other levels of increases. The types of RTS are classified as "increasing" (more than proportional increase), "constant" (proportional increase), and "decreasing" (less than proportional increase). Thus, the RTS measurement suggests implications on how to improve the level of OE by changing the operational size of each organization. A contribution of the DEA measurement is that the approach makes it possible to determine the types of RTS in multiple dimensions of inputs and outputs.

Previous DEA/RTS: In the conventional DEA framework, the measurement of RTS was discussed by Banker [3] and then followed by many other studies (e.g., Chang and Guh [4]). However, at an early stage of research on RTS, the previous research efforts were interested in how to measure the types of RTS on the specific *k*-th DMU (decision making unit). Sueyoshi [5] extended the work by considering DEA duality on RTS in production and cost analyses under the occurrence of multiple solutions and differences between production-based and cost-based RTS estimates. The problem with those previous studies was that all of their discussions belonged to the standard DEA models (e.g., radial and non-radial). Furthermore, they have not incorporated a time horizon, so we cannot use their analytical frameworks with annual changes. See Section I of the book (Sueyoshi and Goto [2]) for a detailed description of the standard RTS measurement.

As an important application, this study examines the RTS of the Chinese electric power industry. The power sector plays a crucial role in supporting economic growth and has gained great research interest. According to the International Energy Agency [6], global annual average power sector investment accounted for almost half of total energy supply investment from 2010 to 2018, and this proportion may increase to two thirds by 2040. Meanwhile, CO_2 emissions from power generation reached 13,818 million tons in 2018, accounting for 41.57% of the world's total [6]. Empirically, this study focuses on the case of China. According to British Petroleum [7], China's electricity generation reached 8534.3 TWh (terawatt-hours) in 2021, accounting for 30.0% of the world total. Thus, China's power sector has attracted great attention from researchers, professionals, and policymakers because of its importance to economic growth and sustainability. Based upon such background, this study evaluates the overall performance and investigates the technology-based measures of China's power sector.

Chinese electric power industry: Currently, global electricity generation is highly linked with but generally separated from electricity transmission. Generally, the power sector consists of generation, transmission, and distribution. According to Newbery [8] and Green [9], many industrialized nations have been under a general deregulation trend to decouple between generation and transmission. It is true for China as well. According to the official websites of the State Council of China and its branches, since 2002, the Chinese government has implemented the deregulation reform, and the power sector has been separated into power and grid companies, decoupling electricity generation and transmission. In China, there are two huge grid companies: "State Grid" and "China Southern Power Grid". The two grid companies operate according to their geographical regions. Meanwhile, power companies are in charge of electricity generation, and there are five large power companies ("China Hua'neng Corporation", "China Datang Corporation", "China Huadian Corporation", "China Guodian Corporation", and "State Power Investment"), four large subsidiary companies, and many small companies.

Purpose of this study: Several previous studies have discussed how to measure the types of RTS. However, their works did not consider a time horizon. The proposed DEA models have two unique features. One feature is that it incorporates a time horizon into their computational processes. The other feature is that it is different from the standard models in terms of factor unification. A problem with the conventional models is that they produce different efficiency measures for input- and output-based orientations. Consequently, they yield different RTS estimates depending upon which production factor (input or output) is used for the RTS measurement. In order to avoid these two difficulties, we develop a new formulation that determines the degree of OE after unifying inputs and outputs. Then, we discuss how to measure the types of RTS over time. As an empirical study, we evaluate the performance of electricity generation and transmission across Chinese provinces. This study utilizes the proposed approach to capture the annual changes in OE and RTS so that we can understand the technology status of China's power sector.

The remainder of this research is structured as follows: Section 2 reviews the previous studies. Section 3 describes methods. Section 4 provides a description of RTS. Section 5 proposes an approach to identifying RTS measurements. Section 6 proposes an application to the Chinese electric power industry. Section 7 summarizes this research and future extensions.

2. Previous Studies

The OE/RTS assessment of China's power sector had two highly linked research groups.

OE/RTS: Table 1 summarizes the previous studies on OE/RTS assessment. The table provided us with two interesting findings. One of the two findings was that OE/RTS have documented wide applications, covering many countries and sectors. The other finding was that OE/RTS may face the possible occurrence of multiple optimal solutions, and many studies have considered how to handle this type of difficulty as a future task.

Table 1. Recent studies on DEA-based RTS measurement.

Articles	Coverage	Addressing Problem of Multiple Solutions	Methods	Orientation	Time Horizon
Taleb et al. [10]	39 airports, Spain, 2008	Yes	Non-radial model	Non-oriented	No
Mousavi et al. [11]	19 commercial branches, Iran, 2018	Yes	Non-radial model	Non-oriented	No
Wang et al. [12]	8 provinces, China, 2013–2017	No	BCC	Input-oriented	No
Kuo et al. [13]	53 ports, Vietnam, 2012–2016	No	Context-dependent DEA	Output-oriented	No
Deng et al. [14]	30 provinces, China, 2016	No	Slack-Based Measure	Non-oriented	No
Sueyoshi and Goto [15]	23 districts, Japan, 2014	Yes	Intermediate approach	Output-oriented	No
Wang et al. [16]	7 companies, China, 2017	No	Slack-Based Measure	Non-oriented	No
Zhou et al. [17]	38 sectors, China, 2010–2014	No	BCC, CCR	Input-oriented	No
Taleb et al. [18]	20 public universities, Malaysia, 2011	No	Radial model	Output-oriented	No
Hatami-Marbini et al. [19]	28 cities, China, 1983	Yes	CCR	Input-oriented	No
Sueyoshi and Wang [20]	855 PV systems, U.S., 2013	Yes	Radial model	Input-oriented	No
Sueyoshi and Goto [21]	160 PV power stations, U.S., Germany	Yes	Radial model	Input-oriented/ Output-oriented	No
Clercq et al. [22]	15 cities, Asia, 2015–2017	No	BCC	Input-oriented	No
Sueyoshi and Yuan [23]	30 provinces, China, 2005–2012	Yes	Radial model	Output-oriented	No
Sueyoshi and Goto [24]	31 chemical and pharmaceutical firms, Japan, 2007–2010	Yes	Radial model	Output-oriented	No
Zhang et al. [25]	37 airport airsides, China, 2009	Yes	BCC, CCR	Output-oriented	No
Du et al. [26]	15 companies, Japan, 1995	Yes	CCR	Input-oriented	No
Korhonen et al. [27]	80 secondary schools, Iran, 1994	Yes	BCC, CCR	Input-oriented	No

Note: BCC: Banker–Charnes–Cooper model. CCR: Charnes–Cooper–Rhodes model.

The contributions of this study is that most previous studies have used radial models. They are classified into input-oriented and output-oriented ones. The different orientations produce different RTS measures. In this regard, Sueyoshi and Goto [21] have discussed how to measure OE/RTS separately, depending on the input or output orientation. Meanwhile, this study unifies the two orientations so that our RTS measure is "unique", not depending upon the input/output orientation. Furthermore, no study has developed the OE/RTS assessment over a reasonable time frame. This study is the first research effort to explore OE/RTS over time.

Power Sector: The second research group was about previous DEA studies on the power sector. Table 2 listed the recent 20 studies. The table indicated four implications. First, many studies have applied DEA to evaluate the performance (OE) of the power sector at various levels of aggregation. Among 20 studies, 11 studies considered the case of China. Thus, China was a research focus because of its large amount of electricity generation and transmission. Second, among all studies, 16 studies considered electricity generation, 15 studies took undesirable outputs (e.g., CO_2 emissions) into account, and only 3 studies analyzed electricity transmission. Third, the previous studies have adopted various DEA models, covering radial, non-radial, and intermediate approaches. Finally, these studies computed only OE, but not RTS.

Table 2. Recent studies on electricity generation or transmission based on DEA measures.

Articles	Coverage	Inputs [a]	Outputs [b]	Methods [c]	Other Assisting Methods	RTS
Zhang et al. [28]	30 provinces, China, 2010–2019	*K*, coal, generation investment, grid investment	*EL*, electricity sold, electricity loss	Network DEA model	Mann-Whitney U test	No
Li et al. [29]	36 countries, 2009–2018	*K*	*EL*	Super-efficiency DEA	Random forest regression	No
Xiao et al. [30]	31 provinces, China, 2013–2017	*K*, *L*	*EL*, CO_2	Epsilon-based measure	Technology gap ratio	No
Eguchi et al. [31]	Power plants, China, 2009–2011	Coal, capital	*EL*	Slack-Based Measure	No	No
Fidanoski et al. [32]	30 countries, 2001–2018	*K*, primary energy trade dependence, primary energy from renewables, electricity from renewables, R&D expenditure rate, urbanization rate	Primary energy intensity, electricity intensity, electricity loss ratio, CO_2	Output-oriented BCC model	No	No
Nakaishi et al. [33]	28 provinces, China, 2014	*K*, coal, electricity used	*EL*	Input-oriented radial model	Tobit regression analysis	No
Tavassoli et al. [34]	16 electricity distribution networks, Iran, 2017	*L*, oil, natural gas, purchases from neighbor, internal consumption, network length	*EL*, electricity transmission, sales volume, service area, loss electricity	Network DEA model	Sensitivity analysis, correlation coefficient	No
Alizadeh et al. [35]	16 regional electrical companies, Iran, 2017–2019	*K*, *L*, fuel	Sold energy, number of customers, distribution transformer, transmission line length	Dynamic DEA model	No	No

Table 2. *Cont.*

Articles	Coverage	Inputs [a]	Outputs [b]	Methods [c]	Other Assisting Methods	RTS
Sueyoshi et al. [36]	30 provinces, China, 2009–2015	*K*, *L*, energy	*EL*, CO_2	Radial model	Discriminant Analysis	No
Cuadros et al. [37]	24 countries, 2000–2016	Gross domestic product per capita, *K*	*EL*, CO_2	Dynamic slack-based DEA model	Moran's Index	No
Mahmoudi et al. [38]	24 thermal power plants, Iran, 2018	*K*, *L*, *C*, fuel, total hours of operation, internal consumption	*EL*, CO_2, revenue	Game DEA model	Principal Component Analysis, Shannon Entropy method	No
Xie et al. [39]	30 provinces, China, 2012–2014	*L*, asset, energy	Generation capacity, CO_2	Directional distance function	Mann-Whitney U test, Kolmogorov-Smirnov test	No
Lee [40]	33 coal-burning power plants, China, 2013	*K*, coal, operating hours	*EL*, CO_2	Nash DEA model	Wilcoxon matched-pairs signed-rank test	No
Halkos and Polemis [41]	789 electric utilities, U.S., 2000–2012	*C*, energy transmission	Utilization of net capacity, CO_2, SO_2, NO_x	DEA window model	Fixed-effects panel data model	No
Sun et al. [42]	30 provinces, China, 2005–2015	*K*, *L*, energy	*EL*, CO_2	Intermediate approach	Mann-Whitney U test	No
Sueyoshi et al. [43]	30 provinces, China, 2015	*K*, *L*, energy	*EL*, CO_2	Radial model, non-radial model, intermediate approach	Mann-Whitney U test	No
Bi et al. [44]	28 coal-fired power plants, China, 2010	*K*, *L*, coal	*EL*, SO_2	Two-stage DEA model	No	No
Guo et al. [45]	44 coal-fired combined heat and power plants, China, 2012	*C*, coal, freshwater, capital depreciation	*EL*, heat, GHG emissions	Slack-Based Measure	Sensitivity analysis	No
Barros et al. [46]	10 hydro-electric power stations, Angola, 2004–2014	*K*, *C*	*EL*	Dynamic RAM model	Simplex regression	No
Arabi et al. [47]	52 power plants, Iran, 2003–2010	*C*, fuel, capital, depreciation	*EL*, SO_2, operational availability, deviation charges	Non-radial model	Malmquist Luenberger indices	No

Note: [a] *K*: capacity. *C*: cost. *L*: labor. [b] *EL*: Electricity. [c] BCC: Banker–Charnes–Cooper model (i.e., standard DEA model). RAM: range-adjusted measure.

In the previous works, Sueyoshi and Goto [21,24] and Sueyoshi and Yuan [23] reviewed the concept of scale efficiency from the perspective of DEA environmental assessment. As an extension, they proposed analytical schemes for how to determine the types of OE/RTS under two disposability concepts. One problem was that the previous studies examined the RTS measurement within the boundaries of radial and non-radial approaches. Meanwhile, Tavassoli et al. [34] considered both electricity generation and transmission simultaneously, which was highly related to this study. However, their study focused on the case of Iran and did not cover RTS measures.

The contributions of the proposed approach are that we address three major problems to be remedied in this study. First, multipliers (weights among inputs and outputs) may become zero, implying that the corresponding factors are not fully utilized in the DEA assessment. In this study, we handle the difficulty by restricting their data ranges. Second, the previous approaches did not have a time horizon, so they could not capture a time shift in the OE/RTS estimates. Finally, it is expected that our application toward the Chinese electric power industry can produce useful information for policy makers by using the updated methodology.

3. Methods

Nomenclatures in this section are summarized as follows:

x_{ijt}: the *i*th input of the *j*th DMU at the *t*th period,
g_{rjt}: the *r*th output of the *j*th DMU at the *t*th period,
ξ_{kt}: the inefficiency score of the *k*th DMU at the *t*th period,
R_i^x: the data range adjustment on the *i*th input,
R_r^g: the data range adjustment on the *r*th output,
λ_{jt}: the intensity variable of the *j*th DMU at the *t*th period,
ε_s: a prescribed very small number (e.g., 0.0001 in this research),
v_i: the dual variable (multiplier) of the *i*th input,
u_r: the dual variable (multiplier) of the *r*th output,
σ: the dual variable that indicates an intercept of the supporting hyperplane.

Note that R_i^x and R_r^g are specified as follows:

$$R_i^x = (m+s)^{-1}\left\{ \max_{jt}\left(x_{ijt}|all\ j\ \&\ all\ t\right) - \min_{jt}\left(x_{ijt}|all\ j\ \&\ all\ t\right)\right\}^{-1} \&$$
$$R_r^g = (m+s)^{-1}\left\{ \max_{jt}\left(g_{rjt}|all\ j\ \&\ all\ t\right) - \min_{jt}\left(g_{rjt}|all\ j\ \&\ all\ t\right)\right\}^{-1}.$$

3.1. Operational Efficiency

We assess the operational efficiency (OE) measure of DMUs by pooling all observations into a cross-sectional structure. The measure serves as a benchmark for our comparison. For example, the measurement examines any difference in the performance of an entity among different groups and different periods using various statistical tests.

This research treats each entity to be evaluated as a DMU. In each DMU, the production technology transforms inputs (X) into outputs (G). Given the observed factors (X and G), we need to evaluate the performance of each DMU by using DEA. Note that we use the subscript "*k*" to indicate the *k*th DMU while "*j*" stands for all DMUs (*j* = 1, …, *n*) to determine an efficiency frontier that is a set of efficient DMUs.

Under the superscript "*v*" stands for variable RTS, we calculate the degree of $OE^v{}_{kt}$ of the *k*th DMU at the specific *t*th period by the following formulation:

$$\begin{array}{ll} Maximize & \xi_{kt} + \varepsilon_s\left(\sum\limits_{i=1}^{m} R_i^x d_{it}^x + \sum\limits_{r=1}^{s} R_r^g d_{rt}^g\right) \\ s.t. & \sum\limits_{t=1}^{T}\sum\limits_{j=1}^{n} x_{ijt}\lambda_{jt} + d_{it}^x + \xi_{kt}x_{\mathrm{ikt}} = x_{ikt}(all\ i), \\ & \sum\limits_{t=1}^{T}\sum\limits_{j=1}^{n} g_{rjt}\lambda_{jt} - d_{rt}^g - \xi_{kt}g_{rkt} = g_{rkt}(all\ r), \\ & \sum\limits_{t=1}^{T}\sum\limits_{j=1}^{n} \lambda_{jt} = 1,\ \lambda_{\mathrm{jt}} \geq 0\ (all\ j\ \&\ t = 1,\ \ldots,\ T), \\ & \xi_{kt}: URS\ (specific\ k\ \&\ t = 1,\ \ldots,\ T), \\ & d_{it}^x \geq 0\ (all\ i\ \&\ t = 1,\ \ldots,\ T)\ \& \\ & d_{rt}^g \geq 0\ (all\ r\ \&\ t = 1,\ \ldots,\ T). \end{array} \tag{1}$$

Here, the left hand side of Model (1) formulates an efficiency frontier of DMUs in all periods (t = 1, . . . , T). The frontier may contain a crossover between and/or among multiple periods so that the frontier consists of the best performers in the T period. Meanwhile, the right hand side indicates the performance of a "specific kth DMU" in a "specific period (t)" to be examined. The remaining parts ($+d^x_{it} + \xi_{kt}x_{\mathrm{ikt}}$ and $-d^g_{rt} - \xi_{kt}g_{rkt}$) indicate the gaps between the efficiency frontier and the observed performance of the specific DMU in multiple dimensional factors. The unified inefficiency (ξ_{kt}) indicates the magnitude of a directional vector toward the frontier. The slacks (${d^x}_{it}$ and ${d^g}_{rt}$) express the remaining parts of the gap that cannot specify the efficiency measure.

Model (1) has two important features. One of the two features is that the efficiency does not depend upon the type of orientation, as mentioned previously. For example, the standard DEA models depend on the type of orientation. The input-oriented efficiency is different from the output-oriented measure. As a result, we have difficulty in understanding which efficiency we use for our DEA assessments. However, Model (1) does not have such difficulty because all factors are unified by a single inefficiency measure (ξ_{kt}), so there is no difference between them. The standard models originated from the ratio form (Charnes et al. [1]), and as a result, they had this methodological feature. However, Model (1) does not have the problem, rather unifying the difference due to the orientation by a single measure. The other is that computational results measured by Model (1) can easily be linked to statistical inferences by applying various non-parametric tests. The methodological benefit makes it possible to examine a null hypothesis about whether there is no difference in efficiency measures among different periods and groups.

The degree of ${OE^v}_{kt}$ of the kth DMU at the tth period is specified by

$$OE^v_{kt} = 1 - \left[\xi^*_{kt} + \varepsilon_s \left(\sum_{i=1}^{m} R^x_i d^{x*}_{it} + \sum_{r=1}^{s} R^g_r d^{g*}_{rt} \right) \right]. \tag{2}$$

Here, the inefficiency measure (${\xi_{kt}}^*$) and all slack variables (${d^{x^*}}_{it}$ and ${d^{g^*}}_{rt}$) are determined by the optimality (*) of Model (1). We obtain these variables within the equation for optimality. The degree is obtained by subtracting the level from unity, as in Equation (2).

The dual formulation of Model (1) becomes as follows:

$$\begin{array}{ll} Minimize & \sum\limits_{i=1}^{m} v_i x_{ikt} - \sum\limits_{r=1}^{s} u_r g_{rkt} + \sigma \\ s.t. & \sum\limits_{i=1}^{m} v_i x_{ijt} - \sum\limits_{r=1}^{s} u_r g_{rjt} + \sigma \geq 0 \ (all\ j\ \&\ all\ t), \\ & \sum\limits_{i=1}^{m} v_i x_{ikt} + \sum\limits_{r=1}^{s} u_r g_{rkt} = 1, \\ & v_i \geq \varepsilon_s R^x_i \ (i = 1, \ldots, m), \\ & u_r \geq \varepsilon_s R^g_r (r = 1, \ldots, s)\ \& \\ & \sigma:\ URS. \end{array} \tag{3}$$

Using Model (3), we can measure the degree of ${OE^v}_{kt}$ of the kth DMU at the tth period by

$$OE^v_{kt} = 1 - \left[\sum_{i=1}^{m} v^*_i x_{ikt} - \sum_{r=1}^{s} u^*_r g_{rkt} + \sigma^* \right]. \tag{4}$$

Here, all the dual variables are determined by the optimality (*) of Model (3). In addition, both Equations (2) and (4) produce the same degree of ${OE^v}_{kt}$ on optimality.

3.2. Durbin-Watson Statistic

With the aim of testing for autocorrelation in the efficiency scores across periods, this study computes the Durbin-Watson statistic after referring to Rutledge and Barros [48].

This statistic can be used as a test for autocorrelation in the efficiency scores across periods. Technically, this statistic can be computed in the following manner in this effort:

$$d_{kt} = \frac{\sum_{t=2007}^{2019} (OE_{kt} - OE_{kt-1})^2}{\sum_{t=2006}^{2019} (OE_{kt})^2}. \tag{5}$$

Equation (5) identifies the following types of autocorrelations: (a) Positive autocorrelation, if d falls into the range of $0 - d_l$; (b) Unable to draw conclusions, if d falls into the range of $d_l - d_u$ or the range of $(4 - d_u) - (4 - d_l)$; (c) No autocorrelation, if d falls into the range of $d_u - (4 - d_u)$; (d) Negative autocorrelation, if d falls into the range of $(4 - d_l) - 4$.

3.3. K-Means Clustering and Group Classification

To summarize the common and heterogeneous characteristics of DMUs, this study adopted the K-means clustering method following Purohit and Joshi [49] and Zhou et al. [50]. Through this method, this study classifies all DMUs into two groups (i.e., Group 1 (low efficiency group) and Group 2 (high efficiency group)), according to their average efficiency scores during 2006–2019. In this way, we can better discover the distribution of efficiency-related measures (e.g., OE and RTS) across DMUs. In addition, as an unsupervised machine learning algorithm, the K-means clustering method minimizes the sum of squared Euclidean distances between each point and the nearest cluster centroid, and this objective function can be formulated as follows:

$$SSE = \sum_{\tau=1}^{2} \sum_{y \in OE_\tau} \|y - \mu_\tau\|^2, \tag{6}$$

where SSE denotes the sum of squared errors and τ stands for different groups. μ_τ is the mean of OE_τ of all observations in group τ.

4. Returns to Scale

4.1. A Visual Description

In returning to the dual formulation (3), Figure 1 visually classifies the three types (i.e., increasing, constant, and decreasing) of returns to scale (RTS). The figure has two coordinates for x and g. However, such a visual description is for our convenience. A contour line connecting {A-B-C-D}, depicts an efficiency frontier at the tth period. The specification of the tth period is not listed in the figure. A production possibility set locates within the southeast region from the efficiency frontier. Further, paying attention to DMU{B}, for example, Figure 1 depicts the three types of slopes and intercepts regarding a supporting hyperplane. Accordingly, Figure 1 classifies the three types of RTS on DMU{B} by the sign of the intercept (σ) of a supporting hyperplane as follows: (a) increasing RTS $\leftrightarrow$ $\sigma < 0$, (b) constant RTS $\leftrightarrow$ $\sigma = 0$ and (c) decreasing RTS $\leftrightarrow$ $\sigma > 0$.

To discuss the relationship between RTS and DEA, we begin with a simple case where an input (x) is used to produce an output (g). In this case, we assume a supporting hyperplane is $vx - ug + \sigma = 0$, or $g = (v/u)x + \sigma/u$. A mathematical requirement, for identifying a supporting hyperplane, is that u should be positive in the sign. The variable (σ) is unrestricted in the sign. However, it should be noted that if u is zero, it is very difficult for us to determine the location of a supporting hyperplane because v/u and σ/u become infinite. Thus, the dual variable related to an output (g) should be strictly positive in determining a supporting hyperplane in a data space of x and g. This finding clearly indicates that Model (3) should incorporate an analytical structure in which the dual variables (u_r for $r = 1, \ldots, s$) should be positive in their signs as proposed in the original standard model, referred to as the "DEA ratio form", that incorporates ε_s (non-Archimedean small number) in the formulation. That is the rationale on why the proposed Models (1) and (3) incorporate the data ranges into their formulations to maintain all positive dual variables.

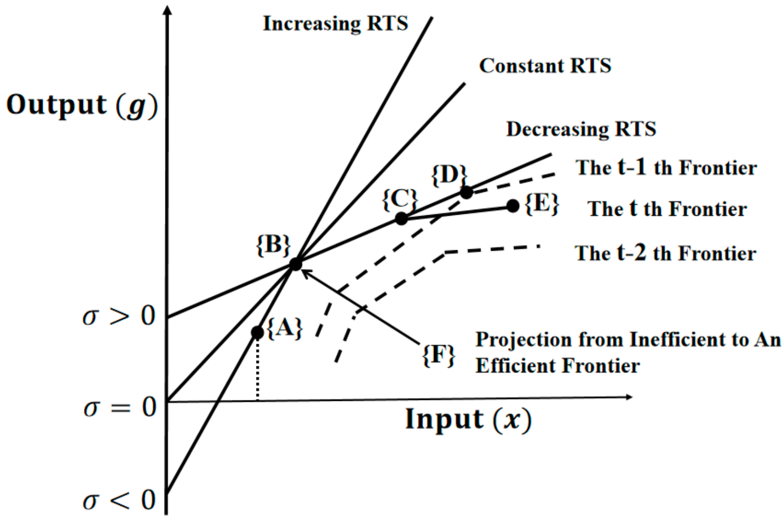


Figure 1. Three types of RTS and supporting hyperplanes. Note: (a) We classify the types of RTS into three cases: increasing, constant or decreasing. (b) Since the efficiency frontier {A-B-C-E} is determined by the best DMU group in multiple periods (t = 1, …, T). The figure exhibits, for example, the three periods {$t-2$, $t-1$ and t). The frontier may contain a group of DMUs among different periods. For example, there is the crossover between the $t-1$ and tth frontiers so that the frontier becomes {A-B-C-E}. (c) The location of a supporting hyperplane is determined by the sign of the intercept (σ). (d) DMU {D} locates the frontier of the $t-1$ period. But, it is not on the frontier during the three periods because of the overlap between the t and $t-1$th periods. The type of inefficient DMU {F} needs to be projected onto DMU {B} and the type is determined on {B} on the frontier.

4.2. A Supporting Hyperplane

Analytically incorporating a time horizon (t), we explore the economic implications of a dual variable(s) on any component of the input and output vectors. We characterize a supporting hyperplane on the kth DMU in Model (3). Further, to initiate our discussion on RTS measured by Model (3), this research describes the mathematical characterization by the following proposition:

Proposition 1. *A supporting hyperplane on the kth DMU at the tth period is mathematically expressed by* $\sum_{i=1}^{m} v_i x_{it} - \sum_{r=1}^{s} u_r g_{rt} + \sigma = 0$ *where* v_i *(i = 1, …, m) and* u_r *(r = 1, …, s) are positive in their signs and measured by Model (3). The two groups of parameters (related to X and G) indicate a vector direction of the supporting hyperplane in the (m + s) dimensional (X, G) space in the tth period. The following equations characterize the supporting hyperplane:*

$$\sum_{i=1}^{m} v_i x_{ijt} - \sum_{r=1}^{s} u_r g_{rjt} + \sigma = 0, j \in RS_{kt} \;\&\; \sum_{i=1}^{m} v_i x_{ikt} + \sum_{r=1}^{s} u_r g_{rkt} = 1, \quad (7)$$

where $RS_{kt} = \left\{ j \mid \lambda_{jt}^{*} > 0,\ j \in J_t \right\}$ *is a reference set for the kth DMU in the tth period measured by Model (1).*

Proof. Sueyoshi and Goto [2] have provided the proof. Q.E.D. □

4.3. Types of RTS and Chi-Square Test

The proposition indicates that Equation (8) expresses an estimated supporting hyperplane on the kth DMU at the tth period by

$$\sum_{r=1}^{s} u_r^* g_{rt} = \sum_{i=1}^{m} v_i^* x_{it} + \sigma^*. \tag{8}$$

From Equation (8), we identify the following types of RTS on the kth DMU at the tth period. See Sueyoshi and Goto [2] for a detailed description.

$$\begin{array}{l} \text{Increasing RTS} \leftrightarrow \text{ An optimal solution of Model (3) satisfies } \sigma^* < 0, \\ \text{Constant RTS} \leftrightarrow \text{ An optimal solution of Model (3) that satisfies } \sigma^* = 0, \\ \text{Decreasing RTS} \leftrightarrow \text{ An optimal solution of Model (3) satisfies } \sigma^* > 0. \end{array} \tag{9}$$

Additionally, after we determine the types of RTS from Equation (9), this study performs the chi-square test with the purpose of finding technology heterogeneity across groups. Technically, this test is as follows:

$$\chi^2 = \sum_{\tau=1}^{2} \sum_{z \in I,C,D} \frac{(OB_{\tau z} - EX_{\tau z})^2}{EX_{\tau z}}, \tag{10}$$

where z stands for the three types (i.e., increasing, constant, and decreasing) of RTS, where I, C, and D represent increasing, constant, and decreasing RTS, respectively. The OB represents the observed numbers of RTS in each group. The EX stands for the number of RTS that each group should have. Through the use of Equation (10), we can statistically test whether there are significant differences in RTS across groups.

4.4. Differences between Proposed Approach and Standard Approach

The standard DEA is classified into two types of projections: input-oriented and output-oriented. Figure 2 visually describes such standard projections and the proposed projection. An efficient frontier is DMUs {A-B-C-D} and an inefficient frontier is DMU {E} in the figure.

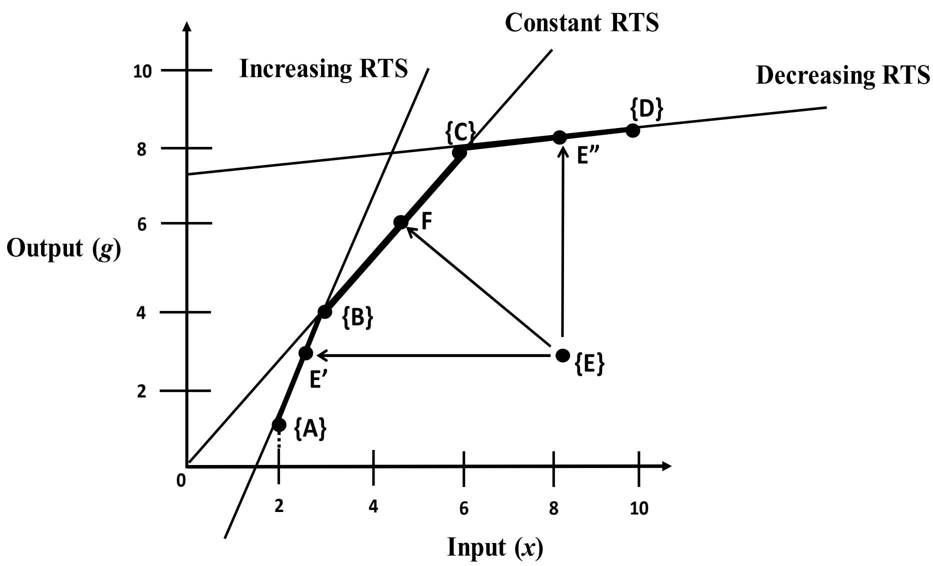


Figure 2. Projections from inefficiency to efficiency: Different types of RTS measures. Note: {E} is an observed DMU while E′, F and E″ are the projected performances of DMU {E} on an efficiency frontier. This study uses { } to indicate the observed performance of a DMU.

The input-oriented model changes the location of {E} to E′ to attain its efficiency. As a result, the type of {E} is evaluated as "increasing". Meanwhile, the output-oriented model changes the location of {E} to E′ so that it is considered "decreasing". The standard DEA models produce different types of RTS. This is problematic. Furthermore, the proposed (input/output unified) model shifts the location to F so that the type of RTS is evaluated as "constant". The assessment proposed in this study is "unique", not depending upon the type of input/output orientation.

5. RTS Measurement under Multiple Solutions

A difficulty of the DEA-based RTS measurement is that it suffers from a possible occurrence of multiple supporting hyperplanes. In order to handle the problem, we need to measure the upper and lower bounds of the intercept (σ), which is the range of the two bounds. In addition, to measure them, we use the following model that is obtained by combining the primal model (1) and the dual model (3):

$$\begin{aligned} & \mathit{Minimize/maximize}\ \sigma \\ & \quad s.t.\ \mathit{constraints\ in\ Models}\ (1)\ \&\ (3), \\ & \quad \xi_{kt} + \varepsilon_s \left(\sum_{i=1}^{m} R_i^x d_{it}^x + \sum_{r=1}^{s} R_r^g d_{rt}^g \right) \\ & \quad = \sum_{i=1}^{m} v_i x_{ikt} - \sum_{r=1}^{s} u_r g_{rkt} + \sigma. \end{aligned} \tag{11}$$

The first two groups of constraints duplicate those of Models (1) and (3). The last constraint indicates that the objective value of Model (1) equals that of Model (3) in measuring the lower and upper bounds of the intercept (σ). The purpose of these constraints is to maintain the primal and dual feasibility in finding the range of σ.

After obtaining $\overline{\sigma}^*$ (the upper bound) and $\underline{\sigma}^*$ (the lower bound) from Model (11), we classify the types of RTS by the following rule:

$$\begin{aligned} & \text{Increasing RTS} \leftrightarrow 0 > \overline{\sigma}^*, \\ & \text{Constant RTS} \leftrightarrow \overline{\sigma}^* \geq 0 \geq \underline{\sigma}^* \text{ and} \\ & \text{Decreasing RTS} \leftrightarrow \underline{\sigma}^* > 0. \end{aligned} \tag{12}$$

Figure 3 visually describes $\overline{\sigma}^*$ (the upper bound) and $\underline{\sigma}^*$ (the lower bound) of the intercept of a supporting hyperplane measured by Model (11) and Equation (12). As discussed previously, the location of a hyperplane depends upon the magnitude of the intercept. The measurement determines the types of RTS in the x-g coordinates.

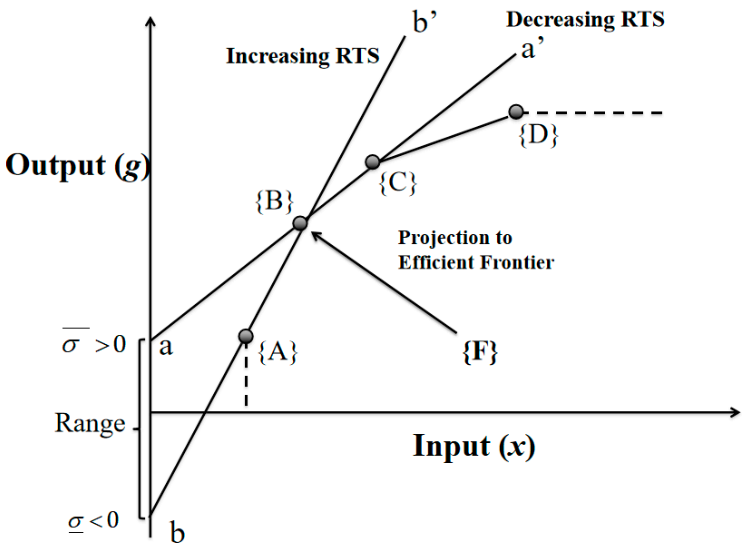


Figure 3. Upper and lower bounds of a supporting hyperplane. Note: An inefficient DMU {F} is first

projected onto {B} for the efficiency enhancement. The efficiency frontier is DMUs {A-B-C-D}. We measure the type of DMU {F} on {B} with its upper and lower bounds. If both are negative, then {F} belongs to increasing RTS. On the other hand, both are positive, then the DMU belongs to decreasing RTS. Equation (12) documents such a classification.

6. Empirical Application

As an empirical application, we consider the performance of electricity generation and transmission across Chinese provinces. Section 6.1 reports the data. Section 6.2 analyzes unified efficiency measures. Section 6.3 discusses RTS estimates.

6.1. Data

This study examines the performance of electricity generation and transmission across Chinese provinces. Due to data availability, this research only considers 30 provinces on China's mainland, and every province is treated as a separate DMU. The data ranges from 2006 to 2019.

In this study, there are three inputs and two outputs. Inputs contain installed capacity, raw coal consumption, and grid investment. For example, as for raw coal consumption, we adopt the raw coal consumed by power plants whose installed capacity exceeds 6000 kW. When calculating grid investment, we adopt the approach of the perpetual inventory system described in Zhang et al. [51]. In this regard, Zhang et al. [51] calculated the depreciation rate of China. Additionally, the authors estimated the capital stock of Chinese provinces at the initial period and then adjusted the capital stock across periods after taking influential factors (e.g., investment and depreciation) into account. During our calculation, this study chooses the GDP price deflators to adjust the price levels, with 2006 as the base year. Further, the outputs include electricity sales by power companies and the number of equivalent users. The data sources are the China Electricity Council (2006–2019) [52]. Table 3 summarizes the descriptive statistics of the production variables.

Table 3. Descriptive statistics of production variables from 2006 to 2019.

Indicators	Inputs			Outputs	
	Installed Capacity	Raw Coal	Grid Investment	Electricity	Equivalent User
	10^3 kW	10^3 tons	10^9 RMB	10^9 kWh	Household
Average	42,034.94	54,897.81	21.69	136.77	168,651.10
Standard Deviation	29,084.67	46,441.00	18.26	107.07	194,549.90
Minimum	2580.00	360.00	1.45	7.44	4674.00
Maximum	140,440.00	267,920.00	130.90	611.80	1,488,872.00

Sources: China Electricity Council (2006–2019) [52].

6.2. OE Measures

This subsection considers the OE measures. The results are reported in Tables 4 and 5 and Figures 4 and 5. These results provided us with four interesting findings. First, there was an upward trend in OE scores. According to the results, China's average OE measures tend to increase over time. The increase corresponded to an improved ability to generate and transmit electricity in China. This finding was not surprising, since China has made a considerable amount of investment in the power sector. However, there were consistent findings in other studies (e.g., Zhang et al. [28] and Eguchi et al. [31]). Both of these two studies found an increasing trend in efficiency measures.

Second, there existed significant differences in OE measures across two groups of provices. In this study, all provinces (DMUs) were classified into two groups, i.e., Group 1 (low efficiency group) and Group 2 (high efficiency group). Group 1 contained 16 provinces, and Group 2 had 14 provinces. From the results, we found that most provinces in Group 1 were located in underdeveloped regions, while most provinces in Group 2 belonged to well-developed regions.

Table 4. OE measures of Chinese provinces.

Groups	Provinces	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Average
Group 1 (low efficiency)	Anhui	0.75	0.72	0.59	0.56	0.62	0.69	0.75	0.81	0.74	0.70	0.64	0.65	0.66	0.67	0.68
	Chongqing	0.67	0.62	0.83	0.68	0.63	0.63	0.60	0.82	0.83	0.80	0.84	0.91	0.91	0.96	0.76
	Gansu	0.88	0.86	0.83	0.76	0.65	0.63	0.72	0.70	0.73	0.69	0.63	0.65	0.70	0.81	0.73
	Guizhou	0.94	0.89	0.88	0.78	0.78	0.72	0.76	0.75	0.82	0.81	0.78	0.74	0.72	0.79	0.80
	Heilongjiang	0.98	0.78	0.69	0.65	0.68	0.72	0.76	0.73	0.84	0.87	0.73	0.72	0.81	1.00	0.78
	Hubei	0.68	0.65	0.64	0.60	0.65	0.64	0.65	0.72	0.62	0.66	0.79	0.87	0.82	0.94	0.71
	Hunan	0.67	0.63	0.55	0.55	0.61	0.65	0.72	0.78	0.92	0.87	0.84	0.84	0.85	0.96	0.75
	Inner Mongolia	0.88	0.89	0.85	0.87	0.98	0.68	0.49	0.57	0.63	0.61	0.55	0.55	0.60	0.70	0.70
	Jiangxi	0.66	0.60	0.70	0.68	0.72	0.80	0.87	0.88	0.90	0.85	0.81	0.77	0.90	0.88	0.79
	Jilin	0.74	0.83	0.77	0.67	0.70	0.62	0.74	0.96	0.81	0.88	0.79	0.79	0.83	1.00	0.80
	Ningxia	0.88	0.96	0.77	0.78	0.75	0.82	0.80	0.78	0.73	0.58	0.51	0.64	0.72	0.84	0.75
	Shaanxi	0.74	0.70	0.62	0.50	0.62	0.63	0.64	0.65	0.71	0.68	0.67	0.67	0.64	0.65	0.65
	Shanxi	0.70	0.68	0.64	0.57	0.60	0.79	0.78	0.96	0.68	0.55	0.51	0.63	0.82	0.80	0.69
	Sichuan	0.80	0.71	0.71	0.60	0.65	0.69	0.68	0.70	0.67	0.74	0.81	0.87	0.87	0.99	0.75
	Tianjin	0.86	0.73	0.68	0.58	0.62	0.66	0.67	0.83	0.75	0.67	0.71	0.69	0.80	0.75	0.71
	Xinjiang	0.92	0.72	0.84	0.62	0.52	0.51	0.54	0.58	0.64	0.62	0.56	0.65	0.57	0.56	0.63
	Group average	0.80	0.75	0.72	0.65	0.67	0.68	0.70	0.76	0.75	0.72	0.70	0.73	0.76	0.83	0.73
Group 2 (high efficiency)	Beijing	1.00	1.00	0.95	0.96	0.99	1.00	1.00	1.00	0.91	0.99	1.00	1.00	1.00	1.00	0.99
	Fujian	0.65	0.64	0.73	0.77	0.75	0.81	0.83	0.82	0.78	0.87	1.00	0.86	0.89	0.94	0.81
	Guangdong	0.93	0.95	0.96	0.96	0.98	1.00	1.00	0.99	1.00	1.00	1.00	1.00	1.00	1.00	0.98
	Guangxi	0.94	0.88	0.91	0.76	0.79	0.85	0.86	0.86	0.93	0.95	0.84	0.85	0.92	0.87	0.87
	Hainan	1.00	0.92	1.00	0.88	0.80	0.83	0.84	0.88	0.97	0.87	0.83	0.89	0.84	0.84	0.88
	Hebei	1.00	0.98	0.97	0.95	0.98	1.00	1.00	0.97	1.00	0.95	0.92	0.95	0.94	0.97	0.97
	Henan	0.69	0.73	0.76	0.77	0.83	0.87	0.87	1.00	0.85	0.79	0.78	0.79	0.82	0.81	0.81
	Jiangsu	0.79	0.84	0.89	0.90	0.94	0.96	0.97	1.00	1.00	0.99	0.99	0.98	0.99	1.00	0.95
	Liaoning	0.94	0.87	0.88	0.81	0.80	0.83	0.81	0.94	0.82	0.84	0.82	0.83	0.84	0.88	0.85
	Qinghai	1.00	0.91	0.90	0.85	0.90	0.87	0.83	0.92	0.92	0.87	0.79	0.88	0.98	0.84	0.89
	Shandong	0.73	0.73	0.75	0.75	0.89	0.94	0.93	0.94	0.86	0.79	0.75	0.74	0.79	0.81	0.81
	Shanghai	0.81	0.87	0.85	0.82	0.91	0.98	0.95	0.98	0.84	0.83	0.86	0.90	0.88	0.92	0.89
	Yunnan	0.73	0.72	0.80	0.71	0.76	0.91	0.83	0.87	0.88	0.85	0.93	0.98	0.95	1.00	0.85
	Zhejiang	0.71	0.75	0.77	0.78	0.86	0.89	0.93	0.93	0.88	0.88	0.89	0.89	0.90	0.97	0.86
	Group average	0.85	0.84	0.87	0.83	0.87	0.91	0.90	0.94	0.90	0.89	0.89	0.89	0.91	0.92	0.89
China's average		0.82	0.79	0.79	0.74	0.76	0.79	0.79	0.84	0.82	0.80	0.79	0.81	0.83	0.87	0.80

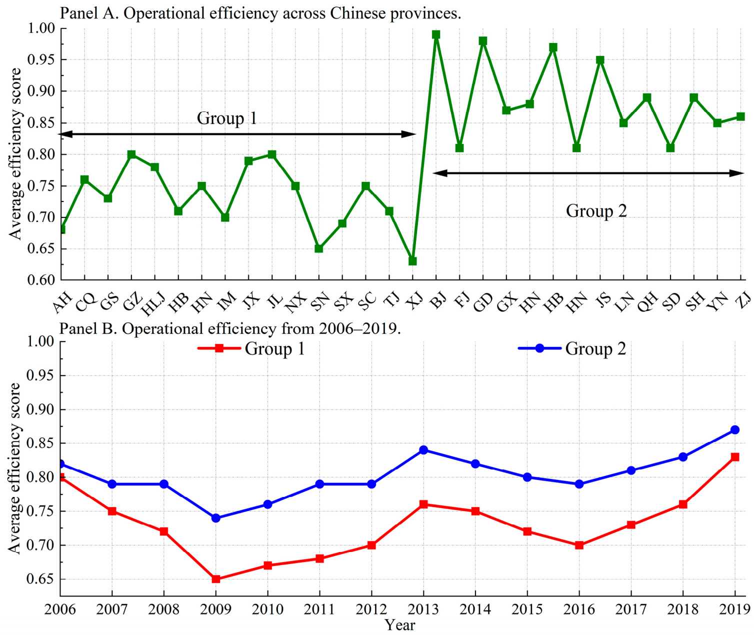


Figure 4. Average OE across Chinese provinces from 2006–2019. Note: AH: Anhui; CQ: Chongqing; GS: Gansu; HLJ: Heilongjiang; HB: Hubei; HN: Hunan; IM: Inner Mongolia; JX: Jiangxi; JL: Jilin; NX: Ningxia; SN: Shaanxi; SX: Shanxi; SC: Sichuan; TJ: Tianjin; XJ: Xinjiang; BJ: Beijing; FJ: Fujian; GD: Guangdong; GX: Guangxi; HN: Hainan; HB: Hebei; HN: Henan; JS: Jiangsu; LN: Liaoning; QH: Qinghai; SD: Shandong; SH: Shanghai; YN: Yunnan; ZJ: Zhejiang.

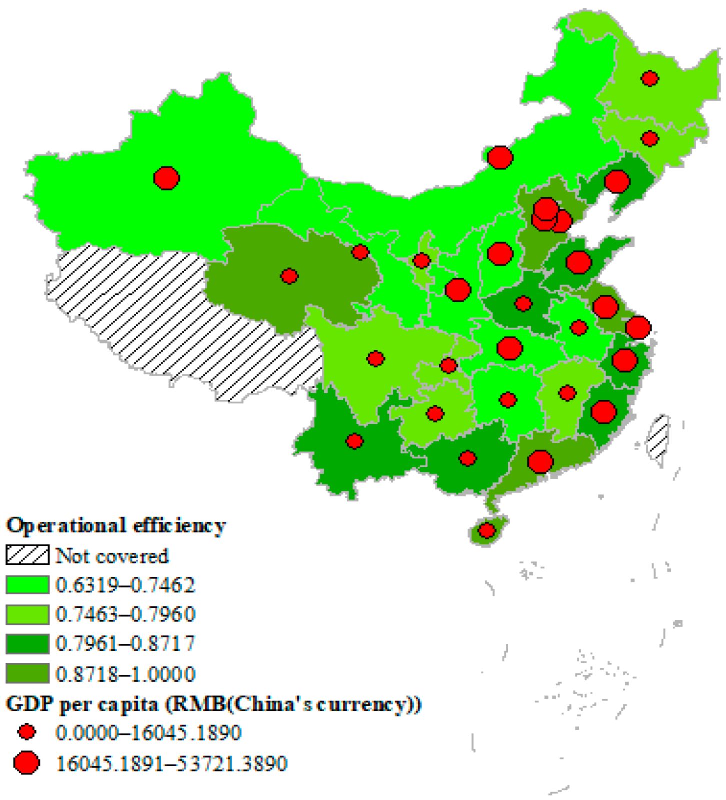


Figure 5. The spatial distribution of operational efficiency and GDP per capita.

Third, large efficiency gaps existed across Chinese provinces. This finding was supported by the proposed approach. According to the results in Table 4, Beijing, Guangdong, Hebei, and Jiangsu were the provinces with the highest average OE measures. All these provinces belonged to Group 2 and were coastal provinces with geographically favorable conditions for economic growth. Among these provinces, Beijing (the Capital of China), Guangdong, and Jiangsu were the most developed regions in China, while Hebei surrounded and supported Beijing. In comparison, some provinces had poor performances in average OE measures and should receive special attention. These provinces contained Xinjiang, Shaanxi, Anhui, Shanxi, and Inner Mongolia. All of these provinces were inland provinces and belonged to Group 1. Furthermore, most of them (Xinjiang, Shaanxi, Shanxi, and Inner Mongolia) were the most important coal or energy producers in China.

Table 5. Summary of efficiency measures in different groups.

Indicators	Group 1 (Low Efficiency)	Group 2 (High Efficiency)
Maximum	1.00	1.00
Minimum	0.49	0.64
Average	0.73	0.89
Standard Deviation	0.05	0.06
Number of efficient observations	2	30

Meanwhile, according to the results in Table 5 and Figure 4 (Panel B), the average OE measures in Group 1 were observed lower than those of Group 2. The standard deviation of OE measures in Group 1 was less than that of Group 2. The most efficient observations were found to belong to Group 2.

Finally, we statistically confirmed that the OE measures of all provinces were positively auto-correlative. Table 6 reported the results of the Durbin Watson statistic. According to the results, all the provinces were observed to be of the first type and thus belonged to a positive autocorrelation. These results indicated that the performance of the electricity generation and transmission systems at one period had positive effects on those at the next period. Consequently, the OE measures had good consistency across periods. However, we also found that there was a strong positive correlation between the OE measures and GDP per capita across Chinese provinces. As demonstrated in Figure 5, the provinces with higher levels of GDP per capita (reflecting higher levels of economic growth) tended to have higher OE measures. For example, four coast provinces (Beijing, Shanghai, Guangdong, and Jiangsu) performed well in both the OE measures and GDP per capita, while another four inland provinces (Sichuan, Gansu, Anhui, and Hunan) performed poorly in terms of these two indicators.

Table 6. Results of Durbin Watson statistic.

Groups	Provinces	*d*	Groups	Provinces	*d*
Group 1	Anhui	0.007	Group 2	Beijing	0.001
	Chongqing	0.015		Fujian	0.007
	Gansu	0.006		Guangdong	0.000
	Guizhou	0.003		Guangxi	0.006
	Heilongjiang	0.016		Hainan	0.005
	Hubei	0.009		Hebei	0.001
	Hunan	0.007		Henan	0.006
	Inner Mongolia	0.023		Jiangsu	0.001
	Jiangxi	0.006		Liaoning	0.004
	Jilin	0.017		Qinghai	0.006
	Ningxia	0.015		Shandong	0.004
	Shaanxi	0.007		Shanghai	0.004
	Shanxi	0.032		Yunnan	0.006
	Sichuan	0.007		Zhejiang	0.002
	Tianjin	0.012			
	Xinjiang	0.026			

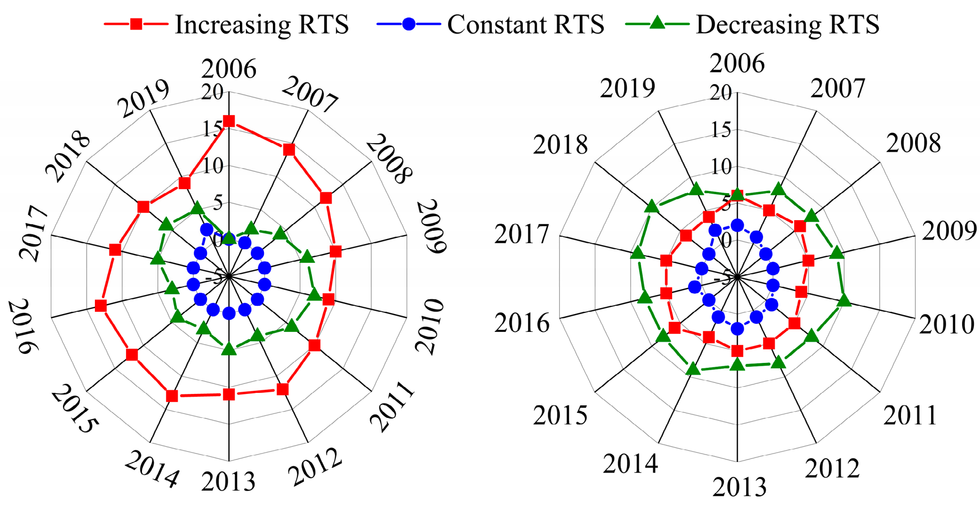
6.3. RTS Measures

This subsection considers RTS measures. The results are reported in Tables 7–9 and Figure 6. These results had three insightful findings.

First, there have been significant changes in the type of RTS over time. According to our results, i.e., the China's total, 55.00% of observations belonged to increasing RTS, 3.10% of observations were under constant RTS, and 41.90% of observations had decreasing RTS. Meanwhile, the numbers of increasing RTS have dropped over time, while those of decreasing RTS have increased. For example, during 2006–2007, more than 63.33% of observations showed increasing RTS. In comparison, this proportion decreased to 43.33% in the year 2019. One possible reason is that some Chinese provinces had relied too much on excessive investments during the examined periods with the purpose of promoting economic growth.

Second, there have been considerable differences in RTS measures across two research groups. As reported in Table 8, for Group 1, 72.32% of the observations belonged to increasing RTS, implying that a DMU could increase its production size to enhance OE because it had enough transmission capacity. In addition, 26.79% of observations showed decreasing RTS, implying that a DMU should reduce the generation to improve its OE. However, things were quite different in terms of Group 2. Only 35.20% of observations faced increasing RTS, and about 59.18% of observations had decreasing RTS. Furthermore, according to Table 9, significant differences in RTS measures were statistically confirmed between the two groups.

Finally, in the type of RTS, we confirmed large differences across Chinese provinces. Some provinces (e.g., Jiangxi, Hainan, Gansu, Qinghai, and Xinjiang) had more occurrences of increasing RTS. These results indicated that these provinces could increase their generation sizes to enhance their OE measures, because they have sufficient transmission capacities. Furthermore, in comparison, some provinces (e.g., Jiangsu, Zhejiang, Shandong, and Guangdong) had more observations of decreasing RTS. These results imply that these provinces should decrease their generation sizes with the purpose of improving their OE measures, due to the fact that they have a limited transmission capacity.



Panel A. Group 1 Panel B. Group 2

Figure 6. The number of DMUs belonging to the three RTS types.

Table 7. The upper bound and lower bound of σ from 2006–2019.

Yeas	2006		2007		2008		2009		2010		2011		2012	
Provinces	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound	Upper bound	Lower bound
Beijing	0.015	−0.246	0.017	−0.300	−0.226	−0.226	−0.216	−0.216	−0.205	−0.205	0.375	−0.203	0.372	−0.174
Tianjin	−0.099	−0.099	−0.206	−0.206	−0.042	−0.042	−0.033	−0.033	0.357	0.357	0.344	0.344	0.334	0.334
Hebei	0.036	−0.045	0.058	0.058	0.055	0.055	0.047	0.047	0.043	0.043	0.135	0.039	0.089	0.078
Shanxi	−0.039	−0.039	0.001	0.001	0.002	0.002	0.002	0.002	0.030	0.030	−0.051	−0.051	−0.048	−0.048
Inner Mongolia	−0.093	−0.093	0.050	0.050	0.043	0.043	0.041	0.041	0.040	0.040	0.030	0.030	−0.033	−0.033
Liaoning	−0.043	−0.043	0.044	0.044	0.042	0.042	0.072	0.072	0.059	0.059	0.116	0.116	0.115	0.115
Jilin	−0.093	−0.093	−0.164	−0.164	−0.117	−0.117	−0.064	−0.064	−0.114	−0.114	−0.043	−0.043	−0.074	−0.074
Heilongjiang	−0.169	−0.169	−0.126	−0.126	−0.060	−0.060	−0.050	−0.050	−0.048	−0.048	−0.051	−0.051	−0.048	−0.048
Shanghai	0.004	0.004	0.004	0.004	0.003	0.003	0.095	0.095	0.003	0.003	−0.037	−0.037	−0.029	−0.029
Jiangsu	0.102	0.102	0.091	0.091	0.090	0.090	0.085	0.085	0.075	0.075	0.068	0.068	0.063	0.063
Zhejiang	0.112	0.112	0.107	0.107	0.101	0.101	0.095	0.095	0.088	0.088	0.081	0.081	0.075	0.075
Anhui	−0.056	−0.056	−0.047	−0.047	−0.036	−0.036	0.003	0.003	0.003	0.003	−0.032	−0.032	−0.029	−0.029
Fujian	−0.023	−0.023	−0.019	−0.019	−0.021	−0.021	−0.018	−0.018	0.013	0.013	−0.014	−0.014	−0.025	−0.025
Jiangxi	−0.083	−0.083	−0.059	−0.059	−0.065	−0.065	−0.049	−0.049	−0.044	−0.044	−0.046	−0.046	−0.041	−0.041
Shandong	0.024	0.024	0.041	0.041	0.069	0.069	0.091	0.091	0.116	0.116	0.100	0.100	0.065	0.065
Henan	0.002	0.002	0.029	0.029	0.048	0.048	0.080	0.080	0.072	0.072	0.081	0.081	0.078	0.078
Hubei	−0.023	−0.023	−0.020	−0.020	−0.018	−0.018	−0.016	−0.016	−0.015	−0.015	−0.013	−0.013	0.032	0.032
Hunan	−0.025	−0.025	−0.021	−0.021	0.015	0.015	0.201	0.201	0.136	0.136	0.123	0.123	−0.018	−0.018
Guangdong	0.079	0.079	0.075	0.075	0.072	0.072	0.080	0.080	0.071	0.071	0.061	0.061	0.112	0.049
Guangxi	−0.040	−0.040	−0.030	−0.030	−0.027	−0.027	−0.024	−0.024	−0.022	−0.022	−0.021	−0.021	−0.035	−0.035
Hainan	−0.446	−1.000	−0.417	−0.417	−0.287	−1.000	−0.352	−0.352	−0.263	−0.263	−0.175	−0.175	−0.309	−0.309
Chongqing	−0.084	−0.084	−0.071	−0.071	−0.064	−0.064	−0.050	−0.050	0.004	0.004	0.008	0.008	−0.050	−0.050
Sichuan	−0.019	−0.019	−0.017	−0.017	0.014	0.014	0.012	0.012	0.127	0.127	0.113	0.113	0.044	0.044
Guizhou	−0.099	−0.099	−0.078	−0.078	−0.074	−0.074	−0.023	−0.023	−0.016	−0.016	−0.015	−0.015	−0.014	−0.014
Yunnan	−0.037	−0.037	−0.029	−0.029	−0.020	−0.020	0.014	0.014	0.012	0.012	0.011	0.011	0.026	0.026
Shaanxi	−0.065	−0.065	−0.055	−0.055	−0.037	−0.037	0.003	0.003	−0.037	−0.037	0.003	0.003	0.001	0.001
Gansu	−0.069	−0.069	−0.059	−0.059	−0.053	−0.053	−0.031	−0.031	−0.031	−0.031	−0.019	−0.019	−0.033	−0.033
Qinghai	−0.105	−0.815	−0.112	−0.112	−0.101	−0.101	−0.139	−0.139	−0.108	−0.108	−0.089	−0.089	−0.098	−0.098
Ningxia	−0.119	−0.119	−0.118	−0.118	−0.093	−0.093	−0.082	−0.082	−0.064	−0.064	−0.102	−0.102	−0.078	−0.078
Xinjiang	−0.328	−0.328	−0.114	−0.114	−0.196	−0.196	−0.073	−0.073	−0.052	−0.052	−0.039	−0.039	−0.029	−0.029

Table 7. *Cont.*

Years	2013		2014		2015		2016		2017		2018		2019	
Provinces	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**	**Upper bound**	**Lower bound**
Beijing	0.427	−0.208	0.334	0.334	−0.248	−0.248	−0.008	−0.331	−0.182	−1.000	−0.009	−0.009	0.844	−1.000
Tianjin	−0.060	−0.060	−0.046	−0.046	0.257	0.257	−0.043	−0.043	−0.041	−0.041	−0.044	−0.044	−0.039	−0.039
Hebei	0.077	0.077	0.373	−0.036	0.078	0.078	0.075	0.075	0.065	0.065	0.060	0.060	0.057	0.057
Shanxi	0.147	0.147	−0.041	−0.041	−0.010	−0.010	−0.009	−0.009	0.023	0.023	0.027	0.027	0.024	0.024
Inner Mongolia	0.022	0.022	0.024	0.024	0.024	0.024	0.020	0.020	0.017	0.017	0.016	0.016	0.364	0.364
Liaoning	0.105	0.105	0.105	0.105	−0.020	−0.020	−0.020	−0.020	−0.019	−0.019	0.026	0.026	−0.018	−0.018
Jilin	−0.075	−0.075	−0.071	−0.071	−0.091	−0.091	−0.073	−0.073	−0.063	−0.063	−0.069	−0.069	0.087	−0.157
Heilongjiang	−0.047	−0.047	−0.086	−0.086	−0.085	−0.085	−0.036	−0.036	−0.034	−0.034	−0.058	−0.058	0.363	−0.326
Shanghai	−0.037	−0.037	0.170	0.170	0.187	0.187	0.156	0.156	0.131	0.131	0.169	0.169	0.014	0.014
Jiangsu	1.000	0.013	0.264	0.048	0.103	0.103	0.236	0.236	0.215	0.215	0.238	0.238	0.979	0.035
Zhejiang	0.070	0.070	0.073	0.073	0.072	0.072	0.058	0.058	0.055	0.055	0.050	0.050	0.048	0.048
Anhui	−0.024	−0.024	−0.026	−0.026	−0.019	−0.019	0.025	0.025	0.023	0.023	0.021	0.021	0.020	0.020
Fujian	−0.013	−0.013	0.010	0.010	−0.022	−0.022	0.872	−0.311	0.029	0.029	0.027	0.027	−0.019	−0.019
Jiangxi	−0.041	−0.041	−0.039	−0.039	−0.035	−0.035	−0.030	−0.030	−0.027	−0.027	−0.029	−0.029	−0.027	−0.027
Shandong	0.061	0.061	0.063	0.063	0.063	0.063	0.058	0.058	0.185	0.185	0.177	0.177	0.170	0.170
Henan	0.844	−0.025	0.076	0.076	0.076	0.076	0.072	0.072	0.067	0.067	0.057	0.057	0.081	0.081
Hubei	0.155	0.155	0.136	0.136	0.165	0.165	−0.041	−0.041	−0.040	−0.040	−0.036	−0.036	0.015	0.015
Hunan	−0.029	−0.029	−0.031	−0.031	−0.029	−0.029	−0.029	−0.029	0.155	0.155	0.050	0.050	−0.026	−0.026
Guangdong	0.052	0.052	0.164	0.037	0.045	0.045	0.044	0.044	0.643	0.004	0.664	0.129	1.000	0.113
Guangxi	−0.019	−0.019	−0.034	−0.034	−0.034	−0.034	−0.030	−0.030	−0.071	−0.071	−0.027	−0.027	0.011	0.011
Hainan	−0.162	−0.162	−0.159	−0.159	−0.155	−0.155	−0.182	−0.182	−0.179	−0.179	−0.159	−0.159	−0.151	−0.151
Chongqing	−0.047	−0.047	−0.045	−0.045	−0.043	−0.043	−0.048	−0.048	−0.041	−0.041	−0.037	−0.037	−0.037	−0.037
Sichuan	0.043	0.043	0.043	0.043	0.253	0.253	0.772	0.772	0.723	0.723	0.649	0.649	−0.059	−0.059
Guizhou	−0.013	−0.013	−0.013	−0.013	−0.024	−0.024	−0.022	−0.022	−0.019	−0.019	0.027	0.027	−0.018	−0.018
Yunnan	0.010	0.010	−0.013	−0.013	0.046	0.046	0.704	0.704	0.656	0.656	0.203	0.203	0.621	−0.062
Shaanxi	0.003	0.003	−0.032	−0.032	−0.024	−0.024	−0.016	−0.016	−0.014	−0.014	−0.013	−0.013	−0.012	−0.012
Gansu	−0.031	−0.031	−0.034	−0.034	−0.064	−0.064	−0.056	−0.056	−0.057	−0.057	−0.037	−0.037	−0.058	−0.058
Qinghai	−0.035	−0.035	−0.076	−0.076	−0.079	−0.079	−0.071	−0.071	−0.073	−0.073	−0.208	−0.208	−0.184	−0.184
Ningxia	−0.070	−0.070	−0.041	−0.041	−0.021	−0.021	−0.019	−0.019	−0.033	−0.033	−0.055	−0.055	0.068	0.068
Xinjiang	−0.013	−0.013	−0.057	−0.057	−0.050	−0.050	−0.044	−0.044	−0.050	−0.050	−0.039	−0.039	−0.036	−0.036

Table 8. Returns to Scale: type classification.

Groups	Provinces	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Group 1	Anhui	I	I	I	D	D	I	I	I	I	I	D	D	D	D
	Chongqing	I	I	I	I	D	D	I	I	I	I	I	I	I	I
	Gansu	I	I	I	I	I	I	I	I	I	I	I	I	I	I
	Guizhou	I	I	I	I	I	I	I	I	I	I	I	I	D	I
	Heilongjiang	I	I	I	I	I	I	I	I	I	I	I	I	I	C
	Hubei	I	I	I	I	I	I	D	D	D	D	I	I	I	D
	Hunan	I	I	D	D	D	D	I	I	I	I	I	D	D	I
	Inner Mongolia	I	D	D	D	D	D	I	D	D	D	D	D	D	D
	Jiangxi	I	I	I	I	I	I	I	I	I	I	I	I	I	I
	Jilin	I	I	I	I	I	I	I	I	I	I	I	I	I	C
	Ningxia	I	I	I	I	I	I	I	I	I	I	I	I	I	D
	Shaanxi	I	I	I	D	I	D	D	D	I	I	I	I	I	I
	Shanxi	I	D	D	D	D	I	I	D	I	I	I	D	D	D
	Sichuan	I	I	D	D	D	D	D	D	D	D	D	D	D	I
	Tianjin	I	I	I	I	D	D	D	I	I	D	I	I	I	I
	Xinjiang	I	I	I	I	I	I	I	I	I	I	I	I	I	I
Aggregation	Increasing RTS	16	14	12	10	9	10	12	11	13	12	13	11	10	9
	Constant RTS	0	0	0	0	0	0	0	0	0	0	0	0	0	2
	Decreasing RTS	0	2	4	6	7	6	4	5	3	4	3	5	6	5
Group 2	Beijing	C	C	I	I	I	C	C	C	D	I	I	I	I	C
	Fujian	I	I	I	I	D	I	I	I	D	I	C	D	D	I
	Guangdong	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Guangxi	I	I	I	I	I	I	I	I	I	I	I	I	I	D
	Hainan	I	I	I	I	I	I	I	I	I	I	I	I	I	I
	Hebei	C	D	D	D	D	D	D	D	C	D	D	D	D	D
	Henan	D	D	D	D	D	D	D	C	D	D	D	D	D	D
	Jiangsu	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Liaoning	I	D	D	D	D	D	D	D	D	I	I	I	D	I
	Qinghai	I	I	I	I	I	I	I	I	I	I	I	I	I	I
	Shandong	D	D	D	D	D	D	D	D	D	D	D	D	D	D
	Shanghai	D	D	D	D	D	I	I	I	D	D	D	D	D	D
	Yunnan	I	I	I	D	D	D	D	D	I	D	D	D	D	C
	Zhejiang	D	D	D	D	D	D	D	D	D	D	D	D	D	D
Aggregation	Increasing RTS	6	5	6	5	4	5	5	5	4	6	5	5	4	4
	Constant RTS	2	1	0	0	0	1	1	2	1	0	1	0	0	2
	Decreasing RTS	6	8	8	9	10	8	8	7	9	8	8	9	10	8

Note: I: increasing returns to scale. C: constant returns to scale. D: decreasing returns to scale.

Table 9. The results of Chi-Square test.

Year	2006	2007	2008	2009	2010	2011	2012	overall
χ^2	12.468 ***	8.769 **	3.214 *	2.143	2.330	2.832	5.105 *	59.890 ***
p-value	0.002	0.012	0.073	0.143	0.127	0.243	0.078	0.000
Year	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	
χ^2	4.470	8.670 **	3.214 *	6.725 **	3.274 *	3.453 *	2.493	
p-value	0.107	0.013	0.073	0.035	0.070	0.063	0.287	

Note: The superscript (***) denotes that we should reject the null hypothesis at a significance level of 1%. The superscript (**) denotes that we should reject the null hypothesis at the significance level of 5%. The superscript (*) denotes that we should reject the null hypothesis at a significance level of 10%.

7. Conclusions

This study considered the DEA based OE/RTS assessment over time. Many previous DEA studies have discussed how to measure the type of RTS. However, their studies did not consider the measurement over a time horizon. The important feature of the proposed RTS measurement was that the proposed models used in this study were different from the standard models in terms of factor unification. A problem of the conventional DEA models was that they produced different efficiency measures between input and output-based measurements. Consequently, they yielded different OE and RTS estimates, depending upon which production factor (input or output) was used for the OE and RTS measurements. In order to avoid the difficulty, it is important to develop a new approach whose efficiency measure is determined after combining them, and then discuss how to measure the types of RTS. As an illustrative example, this study empirically evaluated the performance of electricity generation and transmission in Chinese provinces from 2006 to 2019.

The main empirical evidences are summarized as follows. (a) First, China's electricity generation and transmission systems have improved their performance during the observed periods. The improved performance is possibly because China has invested a large amount of investment in the power sector to support its rapid economic growth. However, it is important for the Chinese central and local governments to pay special attention to the provinces with poor performance. These provinces include Xinjiang, Shaanxi, Anhui, Shanxi, and Inner Mongolia. (b) Second, China has experienced considerable changes in the different types of RTS measures. According to our results, the number of increasing RTS has dropped significantly over time, implying that the increase in the amount of generation may not enhance OE scores. The decreasing RTS indicates that the corresponding provinces should reduce their generation amounts to enhance their OE measures. (c) Finally, we have confirmed significant technological heterogeneity across groups and across Chinese provinces. Additionally, some provinces have experienced more cases of increasing RTS, while other provinces have directed toward decreasing RTS. The underlying policy implication due to the finding is that the former should increase their amounts of generation to enhance the level of OE, while the latter should reduce their generation amounts to enhance the degree. Thus, different provinces may have different strategies to enhance their degrees of OE. Thus, detailed information on production technology for generation and transmission is valuable and important for policy makers in Chinese governments, particularly at the level of provincial governments.

This research has four drawbacks that should be overcome in future extensions. First, it is necessary to compare the proposed OE/RTS measures with the ones obtained from the conventional use of the standard models. This study did not work on such a research effort because of the page limit. Second, it is important for this study to incorporate a description of Chinese regional features so that we can understand the policy implications obtained from this study. Third, we can examine the type of RTS after their convergences when the time is infinite. Usually, the convergences produce group classification [53]. Finally, this type of empirical study needs to compare China with the other industrial nations in Europe, the United States, and Japan in terms of their energy policy developments. All drawbacks will be future extensions of this study.

In conclusion, we hope that this study is useful for Chinese energy policy and look forward to seeing future extensions as discussed in this study.

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References

1. Charnes, A.; Cooper, W.W.; Rhodes, E. Measuring the efficiency of decision making units. *Eur. J. Oper. Res.* **1978**, *6*, 429–444. [CrossRef]
2. Sueyoshi, T.; Goto, M. *Environmental Assessment on Energy and Sustainability by Data Envelopment Analysis*; John Wiley & Sons: London, UK, 2018; pp. 265–350.
3. Banker, R.D. Estimating most productive scale size using data envelopment analysis. *Eur. J. Oper. Res.* **1984**, *17*, 35–44. [CrossRef]
4. Chang, K.P.; Guh, Y.Y. Linear production functions and data envelopment analysis. *Eur. J. Oper. Res.* **1991**, *52*, 215–223. [CrossRef]
5. Sueyoshi, T. DEA duality on Returns to Scale (RTS) in production and cost analyses. *Manag. Sci.* **1999**, *45*, 1593–1608. [CrossRef]
6. International Energy Agency. Available online: https://www.iea.org/reports/world-energy-outlook-2019 (accessed on 22 December 2022).
7. BP (British Petroleum 2022): BP Statistical Review of World Energy. Available online: http://www.bp.com/statisticalreview (accessed on 18 December 2022).
8. Newbery, D. *Electricity Liberalization in Britain and the Evolution of Market Design*; Elsevier: Oxford, UK, 2006; pp. 109–143.
9. Green, R. *Electricity Deregulation in England and Wales*; Springer: Boston, MA, USA, 2012; pp. 179–202.
10. Taleb, M.; Khalid, R.; Ramli, R.; Ghasemi, M.; Ignatius, J. An integrated bi-objective data envelopment analysis model for measuring returns to scale. *Eur. J. Oper. Res.* **2022**, *296*, 967–979. [CrossRef]
11. Mousavi, S.; Amirteimoori, A.; Kordrostami, S.; Vaez-Ghasemi, M. Non-radial two-stage network DEA model to estimate returns to scale. *J. Model. Manag.* **2021**. [CrossRef]
12. Wang, Z.; Li, J.; Liu, J.; Shuai, C. Is the photovoltaic poverty alleviation project the best way for the poor to escape poverty? A DEA and GRA analysis of different projects in rural China. *Energy Policy* **2020**, *137*, 111105. [CrossRef]
13. Kuo, K.; Lu, W.; Le, M. Exploring the performance and competitiveness of Vietnam port industry using DEA. *Asian J. Shipp. Logist.* **2020**, *36*, 136–144. [CrossRef]
14. Deng, F.; Xu, L.; Fang, Y.; Gong, Q.; Li, Z. PCA-DEA-Tobit regression assessment with carbon emission constraints of China's logistics industry. *J. Clean. Prod.* **2020**, *271*, 122548. [CrossRef]
15. Sueyoshi, T.; Goto, M. The intermediate approach to sustainability enhancement and scale-related measures in environmental assessment. *Eur. J. Oper. Res.* **2019**, *276*, 744–756. [CrossRef]
16. Wang, Z.; Hao, H.; Gao, F.; Zhang, Q.; Zhang, J.; Zhou, Y. Multi-attribute decision making on reverse logistics based on DEA-TOPSIS. *J. Clean. Prod.* **2019**, *214*, 730–737. [CrossRef]
17. Zhou, Z.; Xu, G.; Wang, C.; Wu, J. Modeling undesirable output with a DEA approach based on an exponential transformation. *J. Clean. Prod.* **2019**, *236*, 117717. [CrossRef]
18. Taleb, M.; Khalid, R.; Ramli, R. Estimating the returns to scale of an integrated data envelopment analysis model: Efficiency assessment of a higher education institution. *Arab. J. Basic Appl. Sci.* **2019**, *26*, 144–152. [CrossRef]
19. Hatami-Marbini, A.; Beigi, Z.; Hougaard, J.; Gholami, K. Measurement of returns-to-scale using interval data envelopment analysis models. *Comput. Ind. Eng.* **2018**, *117*, 94–107. [CrossRef]
20. Sueyoshi, T.; Wang, M. Measuring scale efficiency and returns to scale on large commercial rooftop photovoltaic systems in California. *Energy Econ.* **2017**, *65*, 389–398. [CrossRef]

21. Sueyoshi, T.; Goto, M. Measurement of returns to scale on large photovoltaic power stations in the United States and Germany. *Energy Econ.* **2017**, *64*, 306–320. [CrossRef]
22. Clercq, D.D.; Wen, Z.; Lu, X.; Caicedo, L.; Cao, X.; Fan, F. Determinants of efficiency in an industrial-scale anaerobic digestion food waste-to-biogas project in an Asian megacity based on data envelopment analysis and exploratory multivariate statistics. *J. Clean. Prod.* **2017**, *168*, 983–996. [CrossRef]
23. Sueyoshi, T.; Yuan, Y. Returns to damage under undesirable congestion and damages to return under desirable congestion measured by DEA environmental assessment with multiplier restriction. *Energy Econ.* **2016**, *56*, 288–309. [CrossRef]
24. Sueyoshi, T.; Goto, M. DEA radial measurement for environmental assessment. *Appl. Energy* **2014**, *115*, 502–513. [CrossRef]
25. Zhang, B.; Wu, H.; Yang, X.; Zhai, W.; Xia, Q.; Li, Y. An estimation of returns to scale of airport airsides under multiple optimal solutions in DEA. *J. Air Transp. Manag.* **2014**, *40*, 149–156. [CrossRef]
26. Du, G.; Lin, W.; Zhang, B. The improved CCR returns to scale method in DEA. In Proceedings of the 2011 2nd International Conference on Artificial Intelligence, Management Science and Electronic Commerce (AIMSEC 2011), Dengfeng, China, 8–10 August 2011; pp. 3490–3494.
27. Korhonen, P.J.; Soleimani-damaneh, M.; Wallenius, J. Ratio-based RTS determination in weight-restricted DEA models. *Eur. J. Oper. Res.* **2011**, *215*, 431–438. [CrossRef]
28. Zhang, R.; Wei, Q.; Li, A.; Ren, L. Measuring efficiency and technology inequality of China's electricity generation and transmission system: A new approach of network Data Envelopment Analysis prospect cross-efficiency models. *Energy* **2022**, *246*, 123274. [CrossRef]
29. Li, W.; Ji, Z.; Dong, F. Global renewable energy power generation efficiency evaluation and influencing factors analysis. *Sustain. Prod. Consum.* **2022**, *33*, 438–453. [CrossRef]
30. Xiao, Q.; Tian, Z.; Ren, F. Efficiency assessment of electricity generation in China using meta-frontier data envelopment analysis: Cross-regional comparison based on different electricity generation energy sources. *Energy Strategy Rev.* **2022**, *39*, 100767. [CrossRef]
31. Eguchi, S.; Takayabu, H.; Lin, C. Sources of inefficient power generation by coal-fired thermal power plants in China. *Renew. Sustain. Energy Rev.* **2021**, *138*, 110562. [CrossRef]
32. Fidanoski, F.; Simeonovski, K.; Cvetkoska, V. Energy Efficiency in OECD Countries. *Energies* **2021**, *14*, 1185. [CrossRef]
33. Nakaishi, T.; Kagawa, S.; Takayabu, H.; Lin, C. Determinants of technical inefficiency in China's coal-fired power plants and policy recommendations for CO_2 mitigation. *Environ. Sci. Pollut. Res.* **2021**, *28*, 52064–52081. [CrossRef]
34. Tavassoli, M.; Ketabi, S.; Ghandehari, M. Developing a network DEA model for sustainability analysis of Iran's electricity distribution network. *Electr. Power Energy Syst.* **2020**, *122*, 106187. [CrossRef]
35. Alizadeh, R.; Beiragh, R.; Soltanisehat, L.; Soltanzadeh, E.; Lund, P.D. Performance evaluation of complex electricity generation systems. *Energy Econ.* **2020**, *91*, 104894. [CrossRef]
36. Sueyoshi, T.; Qu, J.; Li, A.; Xie, C. Understanding the efficiency evolution for the Chinese provincial power industry. *J. Clean. Prod.* **2020**, *277*, 122371. [CrossRef]
37. Cuadros, S.; Rodriguez, Y.; Contreras, J. Dynamic Data Envelopment Analysis Model Involving Undesirable Outputs in the Electricity Power Generation Sector. *Energies* **2020**, *13*, 6624. [CrossRef]
38. Mahmoudi, R.; Emrouznejad, A.; Khosroshahi, H.; Khashei, M.; Parisa, R. Performance evaluation of thermal power plants considering CO_2 emission. *J. Clean. Prod.* **2019**, *223*, 641–650. [CrossRef]
39. Xie, J.; Liang, Z.; Zhang, X.; Zhu, L. Efficiency evaluation of thermal power plants in China based on the weighted Russell directional distance method. *J. Clean. Prod.* **2019**, *222*, 573–583. [CrossRef]
40. Lee, C. Decentralized allocation of emission permits by Nash data envelopment analysis in the coal-fired power market. *J. Environ. Manag.* **2019**, *241*, 353–362. [CrossRef]
41. Halkos, G.E.; Polemis, M.L. The impact of economic growth on environmental efficiency of the electricity sector. *J. Environ. Manag.* **2018**, *211*, 334–346. [CrossRef]
42. Sun, C.; Liu, X.; Li, A. Measuring unified efficiency of Chinese fossil fuel power plants. *Energy Policy* **2018**, *123*, 8–18. [CrossRef]
43. Sueyoshi, T.; Li, A.; Gao, Y. Sector sustainability on fossil fuel power plants across Chinese provinces. *J. Clean. Prod.* **2018**, *187*, 819–829. [CrossRef]
44. Bi, G.; Shao, Y.; Song, W.; Yang, F.; Luo, Y. A performance evaluation of China's coal-fired power generation with pollutant mitigation options. *J. Clean. Prod.* **2018**, *171*, 867–876. [CrossRef]
45. Guo, Y.; Liu, W.; Tian, J.; He, R.; Chen, L. Eco-efficiency assessment of coal-fired combined heat and power plants in Chinese eco-industrial parks. *J. Clean. Prod.* **2017**, *168*, 963–972. [CrossRef]
46. Barros, C.P.; Wanke, P.; Dumbo, S.; Manso, J. Efficiency in Angolan hydro-electric power station. *Renew. Sustain. Energy Rev.* **2017**, *78*, 588–596. [CrossRef]
47. Arabi, B.; Munisamy, S.; Emrouznejad, A.; Toloo, M.; Ghazizadeh, M. Eco-efficiency considering the issue of heterogeneity among power plants. *Energy* **2016**, *111*, 722–735. [CrossRef]
48. Rutledge, D.N.; Barros, A.S. Durbin–Watson statistic as a morphological estimator of information content. *Anal. Chim. Acta* **2002**, *454*, 277–295. [CrossRef]
49. Purohit, P.; Joshi, R. A New Efficient Approach towards K-means Clustering Algorithm. *Int. J. Comput. Appl.* **2013**, *65*, 7–10.

50. Zhou, L.; Zhang, R.; Li, A. New concepts for bootstrap-based cross-efficiency and relative weight analysis and an application to China's governance-finance-innovation-sustainability system. *J. Clean. Prod.* **2022**, *379*, 134549. [CrossRef]
51. Zhang, J.; Wu, G.; Zhang, J. The estimation of China's provincial capital stock: 1952–2000. *Econ. Res. J.* **2004**, *10*, 10.
52. China Electricity Council (2006–2019). Available online: https://bbs.pinggu.org/thread-10851578-1-1.html (accessed on 13 May 2021).
53. Goto, M.; Sueyoshi, T. Sustainable development and convergence under energy sector transition in industrial nations: An application of DEA environment assessment. *Socio-Econ. Plan. Sci.* **2022**, 101316. [CrossRef]