Environmental Science and Pollution Research (2021) 28:52064–52081
https://doi.org/10.1007/s11356-021-14394-4

RESEARCH ARTICLE

Determinants of technical inefficiency in China's coal-fired power plants and policy recommendations for CO_2 mitigation

Tomoaki Nakaishi[1] · Shigemi Kagawa[2] · Hirotaka Takayabu[3] · Chen Lin[4]

Received: 16 December 2020 / Accepted: 10 May 2021 / Published online: 17 May 2021

Abstract

This study applies data envelopment analysis (DEA) to estimate the technical efficiency (TE) and CO_2 emission reduction potential of 1270 coal-fired power plants in 28 Chinese provinces and municipalities. The large dataset used in the study includes 727 combined heat and power (CHP) plants and 543 thermal power plants. Results show an average TE score of 0.57 for the CHP power plants and 0.58 for the thermal power plants, suggesting a significant potential to reduce coal consumption in both types of coal-fired plants. Total CO_2 emission reduction potential was estimated to be 953 Mt-CO_2, or 19% of the total CO_2 emissions of China's electricity and heat producing sectors, indicating that China's coal-fired power plants have a significant potential to mitigate CO_2 emissions through technological improvement. In the second stage of the study, a Tobit regression analysis was conducted to identify the determinants of TE. Factors such as the plant's annual operation rate and capacity utilization rate were found to be significant influences. Based on our results, we propose that the Chinese government create a power distribution structure that generates electricity using technologically efficient equipment in areas rich in coal resources and distributes the generated electricity to other areas of the country.

Keywords Technical efficiency; · Coal-fired power plant; · Data envelopment analysis; · Tobit regression analysis; · CO_2; · China

Introduction

In 2015, China ranked as the world's largest emitter of CO_2, accounting for 28% of global energy-originated CO_2 emissions (International Energy Agency 2020). Approximately 82% of China's total CO_2 emissions were attributable to coal (International Energy Agency 2020). Chinese dependence on coal in its power sector is particularly noteworthy, as approximately 93% of the energy-originated CO_2 emissions associated with the production and supply of the electric power, steam, and hot water originates from coal consumption (Shan et al. 2018). Coal-fired power generation is thus a major source of CO_2 emissions in China.

China has been a party to the Paris Agreement since 2015 and has worked to reduce the amount of territorial CO_2 emissions. However, the Chinese government announced in its 13th 5-Year Plan that it will continue to maintain a coal-based power mix to meet the growing demand for electricity (Central Compilation and Translation Press in China 2016). To mitigate CO_2 emissions from the country's power sector, it will thus be necessary to reduce coal consumption in the coal-fired power generation process through technological improvements, while maintaining the current level of electricity production. As a crucial first step, the current level of efficiency in each of China's coal-fired power plants needs to be evaluated.

A number of previous studies have sought to evaluate technical efficiency (TE) or environmental efficiency (EE) in China's coal-fired power plants using both non-parametric (e.g., data envelopment analysis (DEA)) and parametric (e.g., stochastic frontier analysis (SFA)) frontier-based approaches (e.g., Yang and Pollitt 2009; Yang and Pollitt 2010; Zhao and Ma 2013; Wei et al. 2013; Zhang et al. 2014; Du and Mao 2015; Du et al. 2016; Long et al. 2018b; Wang et al. 2019; Wei and Zhang 2020). However, these studies are limited in four principal respects: (1) many of the

Responsible Editor: Ilhan Ozturk

✉ Tomoaki Nakaishi
yoshizawa.tomoaki.718@s.kyushu-u.ac.jp

1 Graduate School of Economics, Kyushu University, 744 Motooka, Nishi-ku, Fukuoka 819-0395, Japan

2 Faculty of Economics, Kyushu University, Fukuoka, Japan

3 Department of Management and Business , Kindai University , Fukuoka, Japan

4 School of Applied Economics, Renmin University of China, Beijing, China

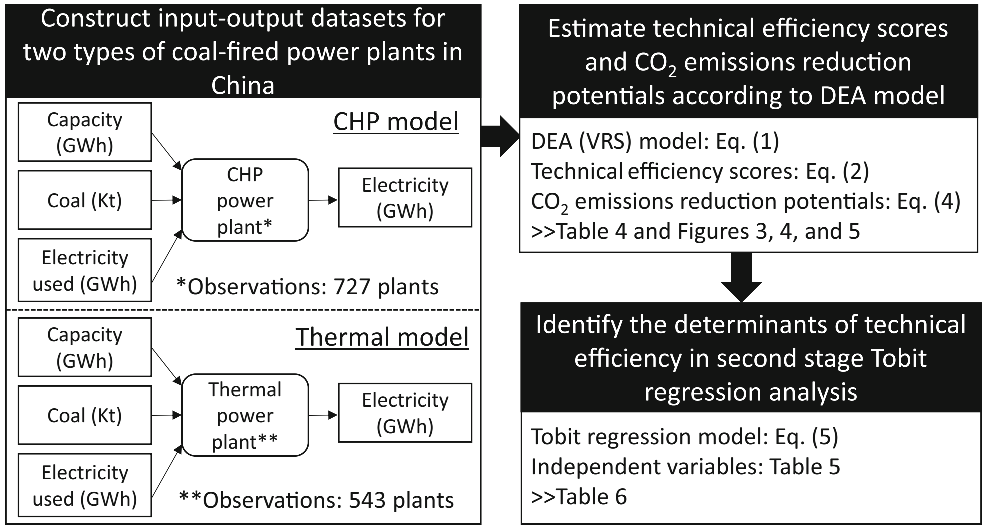


Fig. 1 Research framework

studies use limited sample sizes due to a lack of data availability. Sample size is one of the most important factors in statistical analysis. To the best of our knowledge, Du and Mao (2015) used the largest single-year sample size (648 power plants in 2008); (2) in most of the existing studies, the two types of coal-fired power plants in China (combined heat and power (CHP) plants and thermal power plants) are treated as homogeneous in their efficiency assessments; in other studies, only thermal power plants are analyzed; (3) studies that estimate the CO_2 emission reduction potential of Chinese coal-fired power plants based on TE or EE values using the frontier-based approach are rare. Although Wei et al. (2013), Du and Mao (2015) and Du et al. (2016) estimate potential reductions, their sample sizes are quite limited; and (4) there are very few studies that identify the determinants of estimated TE and EE in China's coal-fired power plants. Identifying the determinants of efficiency would seem essential to accurate decision making by policymakers and plant managers seeking to improve efficiency. Lam and Shiu (2001), Lam and Shiu (2004), Du and Mao (2015), and Long et al. (2018b) are valuable studies that used regression analysis to identify the determinants of efficiency in the second stage of their analysis. However, these studies have clear limitations, which will be discussed in more detail in the "Literature review" section.

Recognizing the aforementioned problems, this study conducts an extensive technical efficiency analysis of 1270 Chinese coal-fired power plants operating in 2011. We first construct a plant-level, cross-sectional database that includes three inputs (coal consumption, installed capacity, and the electricity used in each power plant) and one output (the net electricity produced by the plant) based on the China Electricity Council's 2015 Power Industry Statistics (China Electricity Council 2015). The DEA approach is then used to estimate the TE and CO_2 emissions reduction potential of the coal-fired power plants included in the study (727 CHP plants and 543 thermal power plants across 28 Chinese provinces and municipalities). In the second stage of the analysis, we use a Tobit regression approach to identify the determinants of TE and propose policy measures to improve plant TE and mitigate CO_2 emissions. The principal aim of our study is to provide reliable and crucial information for policymakers seeking to improve TE and mitigate the CO_2 emissions of China's coal-fired power plants through technological improvements. The study's research framework is summarized in Fig. 1.

The remainder of the paper is organized as follows: the "Literature review" section is a brief literature review, the "Methodology" section describes the methodology, the "Data" section explains the data used, the "Results" section provides the empirical results of our efficiency analysis and the estimated CO_2 emissions reduction potential, the "Discussion" section identifies the determinants of technical inefficiency, and the "Conclusion and policy implications" section concludes the paper and outlines the study's policy implications.

Literature review

In recent years, a number of studies have used the frontier-based approach to assess the technical, operational, managerial, and environmental efficiency of China's thermal power generation sector at the provincial level (Lam and Shiu 2001; Lam and Shiu 2004; Kaneko et al. 2010; Zhou et al. 2013; Lin and Yang 2014; Bi et al. 2014; Duan et al. 2016; Yan et al. 2017; Sun et al. 2018) or at the plant level (e.g., Yang and Pollitt 2009; Yang and Pollitt 2010; Zhao and Ma 2013; Wei et al. 2013; Zhang et al. 2014; Du and Mao 2015; Du et al. 2016; Long et al. 2018b; Wu et al. 2019; Wei and Zhang

2020; Nakaishi 2021). Some studies have focused on estimating the EE of Chinese coal-fired power plants (e.g., Yang and Pollitt 2009; Yang and Pollitt 2010; Zhang et al. 2014; Long et al. 2018b), while others have sought to estimate the marginal abatement costs (MAC) of environmental pollutants (e.g., Kaneko et al. 2010; Wei et al. 2013; Du and Mao 2015; Du et al. 2016; Wei and Zhang 2020; Nakaishi 2021). Many of these studies discuss how to effectively reduce CO_2 emissions from Chinese coal-fired power plants based on EE and MAC estimates. However, few studies have focused on identifying the set of determinants that directly influence the TE of China's coal-fired power plants.

Table 1 summarizes the efficiency assessment method, the decision making units (DMUs), the study period, the input and output, and the dependent and independent variables in five related studies (Lam and Shiu 2001; Lam and Shiu 2004; Du and Mao 2015; Long et al. 2018b; Wu et al. 2019) that used the frontier-based approach to analyze the efficiency of China's thermal power sector and subsequently identified the determinants of TE and EE using regression analysis[1].

Lam and Shiu (2001) measured, at the provincial level, the TE of thermal power generation in 30 Chinese provinces in 1995 and 1996 using the variable returns to scale (VRS) model of DEA and found that the TE in municipalities and provinces along the eastern coast of China and in coal-rich areas tended to be higher than the TE in other areas. They also conducted a second stage Tobit regression analysis to identify the determinants of TE and found that fuel use per kWh of electricity (i.e., the FUEL factor) and the ratio of average load to peak load (i.e., the LOAD factor) significantly affected TE. They also found that the provinces and autonomous regions that were not under the control of the state power corporation (i.e., the SPC factor) achieved higher levels of TE and that the presence of foreign investment (i.e., the FOREIGN factor) did not have a significant effect on TE.

Lam and Shiu (2004) is an extension of the earlier study by Lam and Shiu (2001). The data used in this follow-up study were expanded to include time series data from 1995 to 2000. The study examined the TE and total factor productivity (TFP) growth of China's thermal power generation industry in 30 provinces using the DEA approach and DEA-like linear programs. Notably, it was found that municipalities and coastal provinces achieved higher TE and TFP growth during the period under study. Furthermore, according to results from a second stage regression analysis, it was determined that FUEL (i.e., fuel use per kWh of electricity) and UTILIZATION (i.e., the ratio of average annual utilization hours of thermal power generators to total hours in a year) were significant factors influencing the TE of power generation.

Du and Mao (2015) estimated the EE, CO_2 emissions reduction potential, and MAC of CO_2 emissions for Chinese coal-fired power plants using data for 518 (in 2004) and 640 (in 2008) coal-fired power plants and applying a directional distance function (DDF)-based parametric linear programming (PLP) approach. Their empirical results indicated substantial opportunities for CO_2 emissions reduction. In addition, their second stage regression analysis showed that subsidies from the government (i.e., SUBSIDY factor) can improve EE, that the older (i.e., AGE factor) and larger (i.e., SCALE factor) power plants have a lower EE, and that the ratio of coal consumption to fuel consumption (i.e., COAL RATIO factor) negatively affects the EE of power plants.

Long et al. (2018b) investigated EE considering regional heterogeneity for 192 power plants in the Yangtze River Delta of China from 2009 to 2011 using a meta-frontier directional slacks-based measure (SBM). They found that EE increased from 2009 to 2010 and that coal consumption intensity (i.e., COAL INTENSITY factor) negatively impacted EE in their second stage dynamic bootstrap truncation regression analysis.

Wu et al. (2019) considered regional heterogeneity in their investigation of EE at 528 thermal power stations in North China from 2009 to 2011 using a meta-frontier epsilon-based measure (EBM) and found that EE in plants in Beijing and Tianjin was higher than that in other regions and was becoming more divergent. In addition, the results of their second stage bootstrap truncation regression analysis indicated that coal consumption intensity (i.e., COAL INTENSITY factor) negatively affected EE, larger scale (installed capacity above 600 MW) power stations were more environmentally efficient than smaller ones, and longer equipment utilization hours (i.e., UTILIZATION HOUR INTENSITY factor) could increase EE.

Although these five studies are important insofar as they identify some of the determinants of the efficiency score of Chinese thermal power plants as evaluated by the DEA approach using the two-stage DEA model, they have limitations. The data in Lam and Shiu (2001) and Lam and Shiu (2004) are provincial-level data from 1995 to 2000. Du and Mao (2015) used plant-level data, but the included plants account for only 47% (in 2004) and 55% (in 2008) of China's total installed capacity. Long et al. (2018b) and Wu et al. (2019) also used plant-level data; however, the data covered only 192 plants in three provinces and municipalities (Jiangsu, Zhejiang and Shanghai) and 528 plants in six provinces and municipalities

[1] Meta-frontier DEA analysis (O'Donnell *et al*., 2008) is another method that differs from the combined use of DEA analysis and regression analysis to identify the sources of technical inefficiency. For example, Eguchi et al. (2021) applied meta-frontier DEA analysis to three years of input-output data for a number of Chinese power plants (567 plants in 2009, 569 plants in 2010, and 507 plants in 2011) and decomposed the sources of technical inefficiency into regional inefficiency and scale inefficiency. However, meta-frontier DEA analysis is not suitable for identifying multiple determinants, as in this study, as it may lose the robustness of the DEA results due to a decrease in sample size (Eguchi et al. 2021). The combined approach of DEA analysis and regression analysis allows us to test the statistical significance of the analysis results.

Table 1 Previous literature focused on the determinants of efficiency for coal-fired power plants in China

Authors	Journal	Efficiency analysis by frontier approach					2nd stage regression analysis	
		Method	DMU	Year	Inputs	Outputs*	Dependent variable**	Independent variable***
Lam and Shiu (2001)	*Utilities Policy*	DEA (VRS)	30 provinces	1995 1996	Capacity Fuel Labor	Electricity	TE	CAPACITY, FUEL, SPC, FOREIGN, SIZE, AGE, SMALL
Lam and Shiu (2004)	*Review of Industrial Organization*	DEA (CRS and VRS)	30 provinces	1995-2000	Capacity Fuel Labor	Electricity	TE	UTILIZATION, FUEL, SPC
Du and Mao (2015)	*Energy Policy*	PLP (DDF)	518 (in 2004) and 640 (in 2008) coal-fired power plants	2004 2008	Capacity Fuel Labor	Electricity CO_2	EE	SOE, SUBSIDY, AGE, SCALE, COAL RATIO, TIME, EAST, WEST
Long et al. (2018b)	*Renewable and Sustainable Energy Reviews*	SBM-DEA	192 thermal power plants in Yangtze River Delta	2009-2011	Capacity Fuel	Electricity CO_2	EE	COAL INTENSITY, YEAR 2010, YEAR 2011, JIANGSU, ZHIJIANG
Wu et al. (2019)	*Environmental Science and Pollution Research*	EBM-DEA	528 thermal power plant in North China	2009-2011	Capacity Coal	Electricity CO_2 Hour	EE	COAL INTENSITY, UTILIZATION HOUR, INTENSITY, CAPACITY SIZE
This study		DEA (VRS)	1270 coal-fired power plants (727 CHP and 543 thermal)	2011	Capacity CoalElectricity used	Electricity (net)	TE	HOUR, LOAD, FUEL, LARGE, MEDIUM, EAST, CENTRAL

Note*: Electricity is electricity generation; CO_2 is CO_2 emissions

Note**: TE is technical efficiency; EE is Environmental efficiency

Note***: SMALL in Lam and Shiu (2001) is defined as the proportion of generating units smaller than 100 MW; SOE in Du and Mao (2015) is a dummy variable indicating that the plant is state-owned; TIME in Du and Mao (2015) and YEAR in Long et al. (2018b) are dummy variables distinguishing the year of the samples; JIANGSU and ZHIJIANG in Long et al. (2018b) are dummy variables for province. Other factors are explained in the "Literature review" and "Discussion" sections

(Beijing, Tianjin, Hebei, Inner Mongolia, Shandong, and Shanxi), respectively.

Several features of our study define its novelty: First, the dataset is, to the best of our knowledge, the largest plant-level dataset among all related studies. With data for 1270 power plants, it is nearly twice as large as the dataset used by Du and Mao (2015), the largest among the previous studies (648 power plants in 2008), and accounts for 71% of the total installed capacity of China in 2011. Consequently, our study is able to provide more reliable and more detailed information for policymakers seeking to improve TE and mitigate the CO_2 emissions from China's coal-fired power plants through technological improvements.

Second, to the best of our knowledge, our study is the first to evaluate separately the TE of both types of coal-fired plants operating in China—CHP plants and thermal power plants. To date, few studies have evaluated the TE of China's CHP plants. Distinguishing between the two groups makes the technical performance of electricity production within each group more comparable (Zhou et al. 2012). Furthermore, if there are indeed significant technology differences between the two types of plants, any efficiency analysis performed without considering such heterogeneity would be subject to significant bias. Our study is likely the first to provide information on the TE and CO_2 emissions reduction potential of CHP power plants in China.

Third, our study can be regarded as an extension of the literature having a similar research framework, namely, Lam and Shiu (2001) and Lam and Shiu (2004). The data used in the present study's empirical analysis are a decade newer and more detailed at the plant level. By comparing the empirical results of this study to the results of the earlier two studies, we can see how the determinants of TE in China's coal-fired power sector changed over the ten-year period. The detailed plant-level data used in this study can reveal not only differences in TE by region and province, but also differences in TE by power plant. This will enable policy makers to more effectively implement CO_2 emission mitigation policies through technological improvements, with a focus on potential TE and CO_2 emissions reduction at the detailed power plant level.

Methodology

Estimation of technical efficiency

As previously noted, we employ the non-parametric DEA method to measure the TE of coal-fired power plants in China. DEA is a mathematical programming method to assess the relative efficiency of DMUs (Liu et al. 2010). DEA can evaluate the relative efficiency of DMUs in a production possibility set considering the multiple inputs and outputs of the DMUs and without preassigned weights or the need to specify any functional form for the relationships between variables (Thakur et al. 2006).

DEA models can be broadly divided into two types: a CRS model based on an assumption of constant returns to scale (Charnes et al. 1978) and a VRS model based on an assumption of variable returns to scale (Banker et al. 1984). In this study, the VRS model is employed, as the focus is on the electric power industry, where a scale economy works well empirically.

The DEA model can be applied with either an input orientation or an output orientation (Lam and Shiu 2001). In China, power companies can generate only the amount of electricity allocated to the company. Therefore, the only way for a power plant manager to improve the plant's TE is to technologically reduce unnecessary inputs (Song et al. 2015). For this reason, we adopt the input-oriented DEA model, which minimizes inputs while keeping output constant. Following Cook and Zhu (2013), the input-oriented VRS model is given below:

$$\begin{gathered}
\min\ \theta_m - \varepsilon\left(\sum_{i=1}^{I} s_{im}^{-} + \sum_{j=1}^{J} s_{jm}^{+}\right) \\
\text{subject to} \\
\sum_{n=1}^{N} \lambda_n x_{in} = \theta_m x_{im} - s_{im}^{-};\ \ i = 1, 2, \ldots, I \\
\sum_{n=1}^{N} \lambda_n y_{jn} = y_{jm} + s_{jm}^{+};\ \ \ j = 1, 2, \ldots, J \\
\sum_{n=1}^{N} \lambda_n = 1 \\
\lambda_n, s_{im}^{-}, s_{jm}^{+} \geq 0,\ \ n = 1, 2, \ldots, N
\end{gathered} \tag{1}$$

where θ_m is the efficiency value of the DMU$_m$; n is the number of DMUs, assuming the existence of a total of N DMUs; x_{im} and y_{jm} indicate the i^{th} input and j^{th} output factors of DMU$_m$, assuming the existence of a total of I input and J output factors, respectively; λ_n is an endogenously determined weight assigned to all input and output variables in Eq. (1); ε is an infinitesimal positive number to make both the input and output coefficients positive; and s_{im}^{-} and s_{jm}^{+} are non-negative slack variables for inputs and outputs, respectively (Cook and Zhu 2013).

In addition, we define the efficiency score τ_m using the following equation to reflect the value of input and output slack in the efficiency score θ_m (Tsutsui 2001; Fukuyama et al. 2011; Eguchi et al. 2015):

$$\tau_m = \theta_m - \frac{\sum_{i=1}^{I} \frac{s_{im}^{-}}{x_{im}} + \sum_{j=1}^{J} \frac{s_{jm}^{+}}{y_{jm}}}{i + j} \tag{2}$$

As noted, our study focuses on the TE of 1,270 coal fired power plants in China. In Eq. (2), τ_m is interpreted as the TE of power plant m. A τ_m of 1 indicates that power plant m is relatively the most technologically efficient plant. Following Liu et al. (2010), there are three inputs (installed capacity, coal consumption, and electricity used by the coal-fired power plants) and one output (electricity generated by the coal-fired power plants) in the dataset. Thus, in Eq. (1), $I = 3$ and $J = 1$. Two types of plants are included: CHP plants and thermal power plants. A CHP plant produces electricity and heat simultaneously, whereas a thermal power plant produces only electricity. As the two types of power plants use different technologies, it is important to evaluate TE in different production possibility sets[2]. Accordingly, we constructed two types of production possibility sets and DEA models. The first model is the *CHP model*, where the number of DMUs is 727 ($N = 727$). The second model is the *Thermal model,* where the number of DMUs is 543 ($N = 543$).

Estimation of CO_2 emissions reduction potential

As in Cook and Zhu (2013), in the input-oriented DEA model, an efficient DMU with outputs maintained at the current level and which has no potential to reduce inputs is given an efficiency score θ of 1. In other words, inefficient DMUs that have some potential for reducing inputs are given non-negative scores less than 1. In this study, the CO_2 emission reduction potential of each coal-fired power plant was estimated based on its estimated efficiency score. If a particular coal-fired power plant m is identified as inefficient, its current coal consumption x_m^{coal} can be reduced by no more than $\widetilde{x}_m^{coal} = \theta x_m^{coal}$. Thus, the reduction in coal consumption resulting from the increased efficiency of a coal-fired power plant can be calculated as $\Delta x_m^{coal} = x_m^{coal} - \left(\theta x_m^{coal} + s_{coal\ m}^{-}\right)$.

Based on the Intergovernmental Panel on Climate Change (IPCC) guidelines (IPCC 2006), CO_2 emissions Q (t-CO_2) can be calculated as

$$Q = AD \times NCV \times CC \times COF \times \frac{44}{12} \tag{3}$$

where AD is coal consumption (10000t), NCV is net calorific value (TJ/10000t), CC is carbon content (t-C/TJ), COF is the oxidation rate (%), and $\frac{44}{12}$ is the ratio of the mass of one carbon atom combined with two oxygen atoms to the mass of an oxygen atom. Following Shan et al. (2018), in Eq. (2), we set $NCV = 210$, $CC = 26.32$, and $COF = 0.87$. If the coal consumption of power plant m can be reduced by an amount $\Delta x_m^{coal} = x_m^{coal} - \left(\theta x_m^{coal} + s_{coal\ m}^{-}\right)$ by improving its TE, we can use Eq. (3) to estimate RP_m^{CO2}, the corresponding CO_2 emissions reduction potential at inefficient power plant m as follows:

$$RP_m^{CO2} = \Delta x_m^{coal} = x_m^{coal} - \left(\theta x_m^{coal} + s_{coal\ m}^{-}\right) \times NCV \times CC \times COF \times \frac{44}{12} \tag{4}$$

[2] Although the produced heat from CHP power plants should be converted to its electricity equivalent, heat supply data for each CHP plant were unavailable. To overcome this problem, Zhou et al. (2012) suggests that CHP and thermal power plants should be evaluated at separate production frontiers.

Data

To estimate the TE and CO_2 emissions reduction potential of the 1270 coal-fired power plants examined in our study, we constructed a detailed cross-sectional dataset that included three inputs (installed capacity, coal consumption, and electricity used) and one output (net electricity produced) at the plant level from China's 2014 Power Industry Statistics (China Electricity Council2015). Several previous studies (e.g., Yang and Pollitt 2009; Yang and Pollitt 2010; Zhang et al. 2014; Long et al. 2015, 2017, 2018a) have estimated EE based on the directional distance function approach (Chung et al. 1997), each treating CO_2 emissions as an undesirable output. However, according to Eguchi et al. (2021), it is preferable not to consider CO_2 as an undesirable output since a strong linear relationship between coal consumption and CO_2 emissions will occur if the difference in coal quality at each power plant is not taken into account. Since we were unable to identify the types of coal used by the various power plants, we first estimated the TE of each power plant and then calculated the CO_2 emission reduction potential via the IPCC calculation method (Takayabu et al. 2019; Takayabu 2020).

Tables 2 and 3 show the summary statistics for the input factors (installed capacity (MW), coal consumption (kt), and electricity used (GWh) by the power plant) and the output factor (net electricity produced (GWh) by the power plant) of the CHP plants and thermal power plants, respectively. In 2014, there were nearly 2000 coal-fired power plants in 31 provinces in China (China Electricity Council 2015). However due to a lack of data, we are unable to include all of the power plants in this analysis. Nevertheless, our sample accounts for 71% of the total installed capacity in China in 2011 (China Electricity Yearbook committee 2012).

Tables 2 and 3 give the summary statistics of the input and output factors for different regions in China. As per Hu and Wang (2006), the 28 provinces and municipalities of China are divided into three major areas—EAST, CENTRAL, and WEST (Fig. 2). Compared to other areas, the EAST is more economically developed, while the CENTRAL area has substantially more coal sources.

Table 2 shows that there are many more CHP power plants in the EAST, and that the thermal power plants are mostly located in the EAST and CENTRAL areas. Based on the average scale of the CHP plants, the CHP plants in the WEST are relatively larger than the CHP plants in the other areas, and the plants in the EAST are relatively smaller than the CHP plants in the other areas. On the other hand, with respect to the average scale of the thermal power plants, the plants in the WEST are relatively smaller than the thermal plants in the other areas, while the plants in the EAST are relatively larger than the thermal plants in the other areas. A comparison of the two types of plants reveals that the number of CHP power plants is greater than the number of thermal

Table 2 Summary statistics for the 727 CHP power plants in China

Region	Descriptive statistics	Installed capacity (MW)	Coal consumption (kt)	Electricity used (GWh)	Net electricity generated (GWh)
EAST	Mean	100.70	239.89	34.41	440.28
	SD	202.61	531.37	74.88	996.95
	Minimum	3.00	0.56	0.08	0.93
	Maximum	1730.00	3213.58	475.15	6608.48
CENTRAL	Mean	260.42	701.25	91.83	1139.52
	SD	284.21	835.65	112.49	1409.50
	Minimum	6.00	2.47	0.61	4.00
	Maximum	1200.00	4059.77	666.05	6989.71
WEST	Mean	386.48	934.43	134.88	1878.27
	SD	270.59	659.21	93.57	1488.32
	Minimum	30.00	78.53	9.25	63.59
	Maximum	929.00	2717.40	388.48	6309.42
ALL	Mean	142.70	357.06	49.44	630.05
	SD	237.38	646.87	89.08	1169.48
	Minimum	3.00	0.56	0.08	0.93
	Maximum	1730.00	4059.77	666.05	6989.71

power plants, whereas the scale of thermal power plants is much larger than the scale of CHP power plants.

Results

Efficiency analysis

Figures 3 and 4 are histograms showing the estimated TE scores of the 728 CHP plants and 547 thermal power plants, respectively. As can be seen here, there is a comparatively wide disparity in the TE scores of the CHP power plant group (Fig. 3), while the TE scores of the thermal power group are fairly concentrated between 0.4 and 0.8 (Fig. 4).

We also find a wider gap in the relative TE scores of the CHP power plants in the EAST (Fig. 3), while the relative TE gap between the thermal power plants is particularly higher in the CENTRAL and WEST areas compared to the EAST (Fig. 4).

Table 3 Summary statistics for the 543 thermal power plants in China

Region	Descriptive statistics	Installed capacity (MW)	Coal consumption (kt)	Electricity used (GWh)	Net electricity generated (GWh)
EAST	Mean	935.58	2397.38	289.90	5084.69
	SD	839.53	2101.85	247.44	4792.26
	Minimum	6.00	4.23	0.51	9.49
	Maximum	4400.00	10840.73	1441.68	25617.26
CENTRAL	Mean	737.51	1892.28	247.39	3600.45
	SD	654.88	1883.66	215.06	3456.40
	Minimum	6.00	1.07	0.10	0.72
	Maximum	4800.00	15653.13	1268.74	28236.94
WEST	Mean	724.88	2007.71	260.24	3380.71
	SD	620.11	1646.57	216.01	3037.82
	Minimum	12.00	25.97	1.90	17.10
	Maximum	2475.00	6985.20	1285.81	15413.05
ALL	Mean	817.47	2120.92	267.16	4178.64
	SD	738.70	1955.48	230.02	4079.66
	Minimum	6.00	1.07	0.10	0.72
	Maximum	4800.00	15653.13	1441.68	28236.94

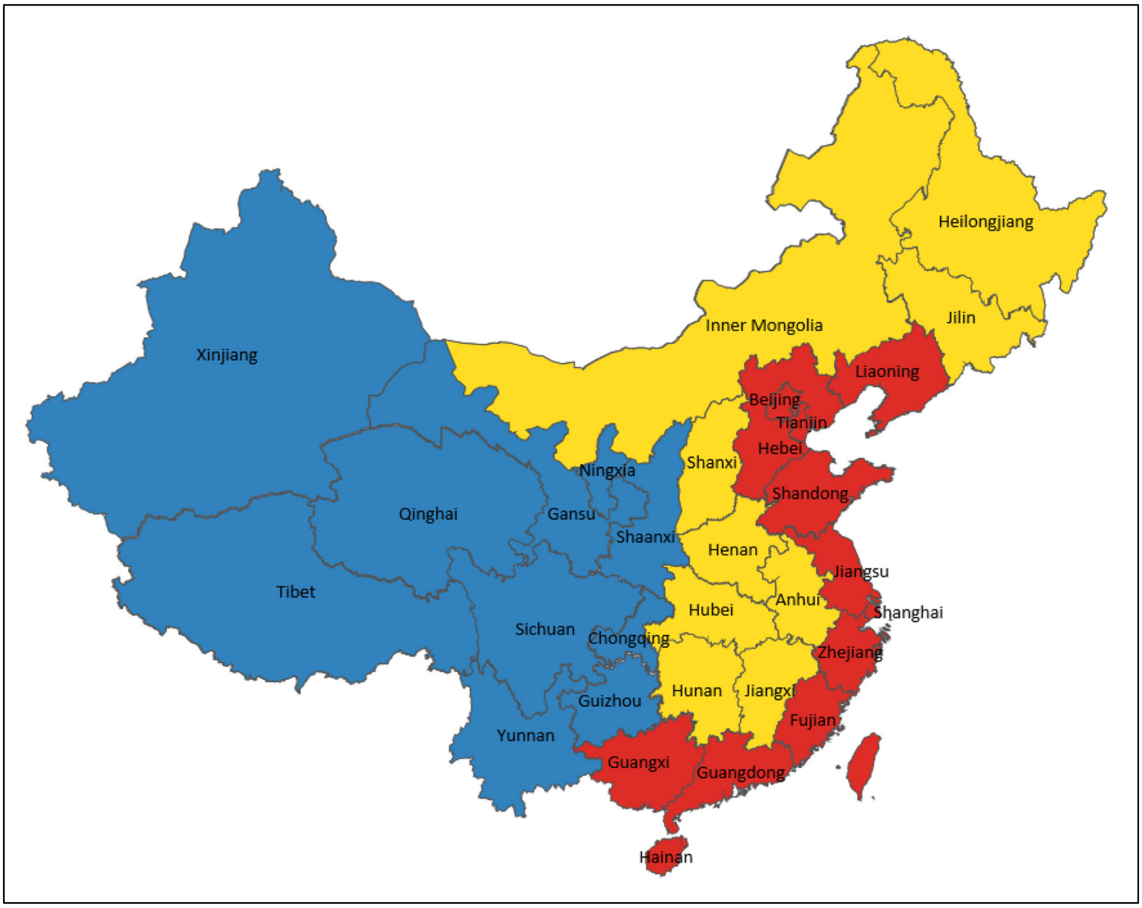
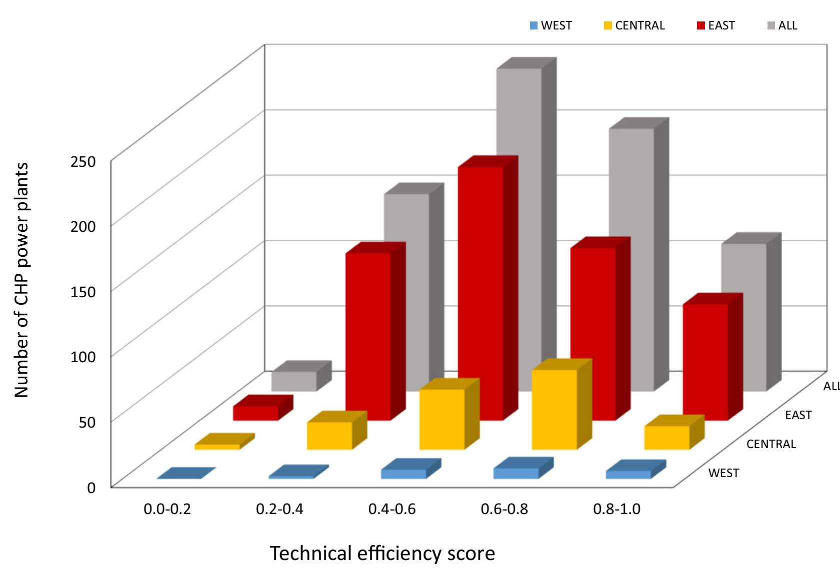


Fig. 2 Map of Chinese provinces and regions. The blue, yellow, and red colors indicate the WEST, CENTRAL, and EAST areas respectively

Table 4 summarizes the results of our TE analysis. The overall average TE score is 0.57 for the CHP plants and 0.58 for the thermal plants, indicating that the 727 CHP plants and 543 thermal plants have the potential to reduce inputs, including coal input, by 43% and 42%, respectively, while maintaining the current level of power production.

Lam and Shiu (2001) found that the efficiency scores for the EAST and CENTRAL areas are higher than the efficiency score for the WEST. However, in the current study, we found that in the CHP model, the highest TE score was in the WEST (0.68), followed by the CENTRAL (0.60) and EAST (0.56) areas (Table 4). This result indicates that the conclusion in

Fig. 3 Histograms of technical efficiency scores for CHP power plants in the three areas



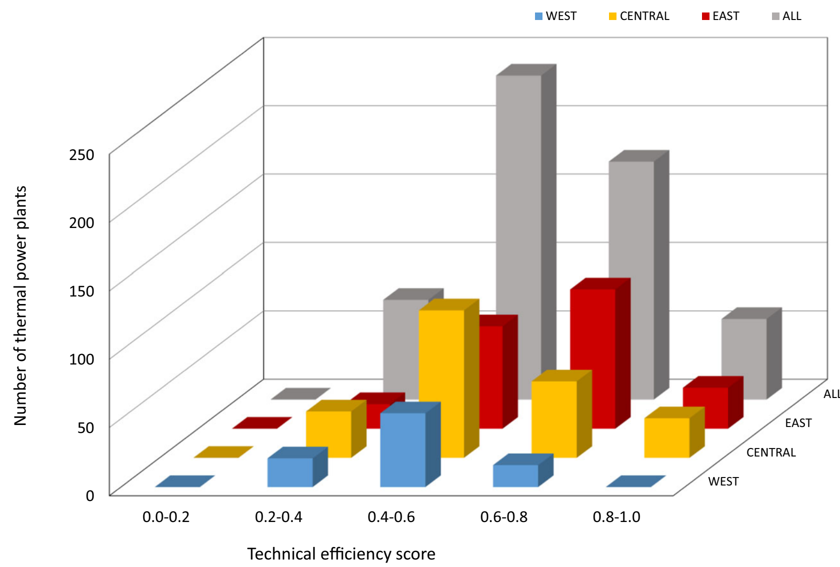


Fig. 4 Histograms of technical efficiency scores for thermal power plants in the three areas

prior studies that power plants located in the EAST and CENTRAL regions have higher TE scores does not hold for CHP power plants. Our results in the thermal model were more consistent with those reported in prior studies: the highest TE score (0.63) was in the EAST, as in previous studies, followed by the CENTRAL (0.57) and WEST (0.50) areas (Table 4).

In the CHP model, Hunan Province had the highest TE score (0.85), followed by Guangdong Province (0.82), and Beijing (0.80) (Table 4). Sichuan had the lowest score (0.31), followed by Hebei (0.48), and Shandong (0.51). In the thermal model, Jiangxi (0.92) and Hunan (0.85) had the highest TE scores among the provinces and municipalities, while Yunnan (0.45), Sichuan (0.46), Inner Mongolia (0.47), and Hebei (0.48) had the lowest scores[3].

Tables 7 and 8 in the Appendix list the power plants with the highest TE scores (i.e., $\tau = 1$) in the CHP and thermal models. Most of these high-scoring plants are in the EAST and CENTRAL areas. These plants form a production possibility frontier in each of the DEA models. In order to improve their TE, plants determined to be technically inefficient (i.e., $\tau \leq 1$) should refer to the practices of the more efficient plants. Table S1 in Supporting Information provides the TE scores for all the power plants included in the study.

CO_2 emissions reduction potential

Table 4 also shows the value of the average (per plant) CO_2 emissions reduction potential for each province/municipality and each area calculated from the results of the TE analysis. If the average TE of all the technically inefficient CHP and thermal power plants in each province were raised to the level of the plants with the highest efficiency scores listed in Tables 5 and 6, the CHP plants would achieve an average CO_2 reduction of 178.25 kt; similarly, the thermal plants would achieve an average CO_2 reduction of 1516.14 kt. Based on these numbers, thermal power plants show substantially greater potential to reduce CO_2 emissions. The indication here is that the size of the power plant has a material effect on its CO_2 emissions reduction potential (see Tables 2 and 3).

In the CHP model, the provinces/municipalities with the highest average CO_2 emissions reduction potential are Guangxi (624.03 kt-CO_2), Inner Mongolia (546.48 kt-CO_2), and Jilin (519.89 kt-CO_2); in the thermal model, Yunnan (3073.41 kt-CO_2), Guizhou (2912.07 kt-CO_2), and Inner Mongolia (2441.98 kt-CO_2) have the highest average potential. The provinces/municipalities with the lowest average CO_2 emissions reduction potential are Hunan (0.80 kt-CO_2), Zhejiang (39.87 kt-CO_2), and Jiangsu (59.18 kt-CO_2) in the CHP model, and Jiangxi (11.29 kt-CO_2) and Hunan (46.80) in the thermal model. Note that the provinces with low TE scores do not necessarily have large CO_2 emissions reduction potential. If the efficiency assessment in the DEA framework is used for environmental policy decisions, calculating the efficiency score alone is insufficient; it is also important to estimate the potential for reducing CO_2 emissions.

The shaded map in Fig. 5 indicates the cumulative value of CO_2 emissions reduction potential by province. As shown here, the cumulative value of CO_2 emissions reduction potential in Inner Mongolia is 119,247.99 kt-CO_2, which is significantly higher than the other provinces and municipalities. Following Inner Mongolia, in descending order, are Shanxi (96502.03 kt-CO_2) and Shandong 80085.64 kt-CO_2. Jiangxi Province has the lowest CO_2 emissions reduction potential, most likely because of the small dataset. The total CO_2 emissions reduction potential of the 1270 plants is 953 Mt-CO_2, which accounts for approximately 19% of the total CO_2

[3] The TE scores of Hunan and Sichuan provinces in the CHP model, as well as Jiangxi province in the thermal model, should be interpreted with caution due to the small dataset.

Table 4 Average technical efficiency scores and average CO_2 emissions reduction potential of CHP and thermal power plants in China

Region	Province and municipality	CHP power plants			thermal power plants		
		Obs.	TE	CO_2 emissions reduction potential (kt-CO_2)	Obs.	TE	CO_2 emissions reduction potential (kt-CO_2)
EAST	Beijing	5	0.80	302.50	0	-	-
	Tianjin	12	0.64	241.40	2	0.58	2330.49
	Hebei	17	0.48	340.71	7	0.46	755.65
	Liaoning	55	0.57	277.83	22	0.56	1870.53
	Shanghai	4	0.76	91.41	11	0.73	979.46
	Jiangsu	133	0.61	59.18	46	0.68	1376.99
	Zhejiang	88	0.58	39.87	29	0.72	947.62
	Fujian	7	0.46	97.64	11	0.66	1541.98
	Shandong	223	0.51	101.90	44	0.60	1303.70
	Guangdong	9	0.82	202.49	42	0.58	1430.36
	Guangxi	1	0.69	624.03	9	0.57	1955.55
	Hainan	0	-	-	2	0.60	2079.22
	Sub total	554	0.56	113.86	225	0.63	1372.70
CENTRAL	Shanxi	13	0.56	375.76	49	0.49	1869.74
	Inner Mongolia	35	0.66	546.48	41	0.47	2441.98
	Jilin	29	0.59	519.89	4	0.53	1745.13
	Heilongjiang	51	0.55	216.06	24	0.51	1026.64
	Anhui	5	0.68	107.12	35	0.68	1200.60
	Jiangxi	0	-	-	3	0.92	11.29
	Henan	16	0.63	438.31	40	0.58	1436.20
	Hubei	0	-	-	15	0.60	1475.46
	Hunan	1	0.85	0.80	16	0.85	46.80
	Sub total	150	0.60	384.38	227	0.57	1529.21
WEST	Sichuan	1	0.31	96.02	14	0.46	1370.81
	Guizhou	0	-	-	17	0.48	2912.07
	Yunnan	0	-	-	12	0.45	3073.41
	Shaanxi	7	0.68	457.81	25	0.50	1426.68
	Gansu	9	0.69	449.12	7	0.57	2007.08
	Qinghai	0	-	-	2	0.49	1444.85
	Xinjiang	6	0.74	251.36	14	0.54	649.63
	Sub total	23	0.68	384.82	91	0.50	1838.22
	Grand total	727	0.57	178.25	543	0.58	1516.14

Note: Obs. refers to observations; TE refers to technical efficiency

emissions from China's electricity and heat producing sector in 2011 (International Energy Agency 2020). The provinces and municipalities along the coast of China and north of the Yangtze River tend to have a relatively high potential for reducing CO_2 emissions.

Tables 9 and 10 in the Appendix list the 10 power plants in each model with the highest potential for reducing CO_2 emissions. In the CHP model, Fuxin Jinshan Coal Thermal Power Co., Ltd. in Liaoning has the largest CO_2 emissions reduction potential (2759.27 kt-CO_2). In the thermal model, Inner Mongolia Huolinhe Hong Jun Aluminum Electric Company has the largest reduction potential (7867.88 kt-CO_2). Thus, the thermal power plants show a relatively high CO_2 emissions reduction potential compared to the CHP power plants. In both models, the power plants in Inner Mongolia and Liaoning tend to have significant potential to reduce CO_2 emissions. Table S1 in Supporting Information provides the CO_2 emissions reduction potential of all the power plants.

Discussion

To identify the determinants of the TE score produced by the DEA model, we conducted a Tobit regression analysis using

Table 5 Summary statistics for the Tobit regression independent variables

Plant type	Descriptive statistics	HOUR	LOAD	FUEL	LARGE	MEDIUM	EAST	CENTRAL
CHP	Mean	0.45	0.98	0.57	0.02	0.09	0.76	0.21
	SD	0.23	0.13	0.31	0.12	0.29	0.43	0.40
	Minimum	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Maximum	0.98	1.99	3.79	1.00	1.00	1.00	1.00
Thermal	Mean	0.60	0.98	0.57	0.37	0.26	0.41	0.42
	SD	0.16	0.12	0.28	0.48	0.44	0.49	0.49
	Minimum	0.01	0.18	0.02	0.00	0.00	0.00	0.00
	Maximum	0.96	1.81	2.92	1.00	1.00	1.00	1.00

the TE scores of the CHP model and the thermal model as the dependent variable.

We assumed that the TE of a power plant is determined by the following five factors (variables):

(1) *HOUR:* an independent variable indicating the annual operating rate of the power plant obtained by dividing the annual operating time of the plant by the total hours in the year. In the second stage of the empirical study by Lam and Shiu (2004), this variable proved to have a significant effect on the provincial-level TE of the power plants[4].

(2) *LOAD*: an independent variable indicating the capacity utilization ratio of the power plant, calculated as the average load of the power plant divided by the maximum load of the plant. A similar independent variable was used in Lam and Shiu (2001), where it was shown to have a significant effect on provincial-level TE scores[5]. Horii (2007) states that the stagnant growth in electricity demand since 2008 due to the effects of the international financial crisis may lead to excess capacity in the future. Thus, if the two independent variables, *HOUR* and *LOAD*, significantly affect the TE score of a power plant, we can conclude that there is a problem of excess capacity in China.

(3) *FUEL*: an independent variable indicating the quality of coal and the amount of coal consumption (kt) required to produce 1 GW of electricity. The empirical analyses by Lam and Shiu (2001) and Lam and Shiu (2004) found that this variable had a negative effect on the provincial TE scores. Thus, if this variable is found to have a significant effect on the TE score of a power plant, it can be inferred that the quality of coal used in the electricity generation process is an effective factor for improving the TE of power plants.

(4) *LARGE* and *MEDIUM:* dummy variables intended to account for differences in the size of power plants in China. Based on the results of their empirical study, Zhan *et al.* (2014), found that power plants with greater installed capacity have higher TE scores. Similarly, we anticipate that plant size will affect the technical efficiency of both the CHP power plants and the thermal power plants. Following the definition used by the China Electricity Yearbook committee (2018), *LARGE* includes plants with installed capacities of 1000 MW

Table 6 Estimation results from the Tobit regression analysis

Variable	CHP model	Thermal model
β_0 (CONSTANT)	−0.092*	0.218***
	(−1.925)	(3.822)
β_1 (HOUR)	0.662***	0.230***
	(30.906)	(6.151)
β_2 (LOAD)	0.439***	0.223***
	(12.011)	(4.590)
β_3 (FUEL)	−0.149***	−0.174***
	(−9.578)	(-7.474)
β_4 (LARGE)	0.128***	0.100***
	(3.253)	(6.711)
β_5 (MEDIUM)	0.087***	0.024
	(5.005)	(1.539)
β_6 (EAST)	0.014	0.090***
	(0.515)	(5.222)
β_7 (CENTRAL)	0.010	0.065***
	(0.361)	(3.851)
Log-likelihood	−413.460	−278.424
N	727	543

Note: *t*-values for the independent variables are shown in parentheses. Superscript *** represents significance at the 1% significance level. Superscript * represents significance at the 10% significance level

[4] In Lam and Shiu (2004), UTILIZATION, an independent variable similar to *HOUR* in this study, was used in the regression model. UTILIZATION is defined as the ratio of the average annual utilization hours of the thermal power plants in each province to the total hours in a year.

[5] In Lam and Shiu (2001), CAPACITY, an independent variable similar to *LOAD* in this study, was used in the regression model. CAPACITY is defined as the average load of thermal power plants in each province divided by the average installed capacity in each province.

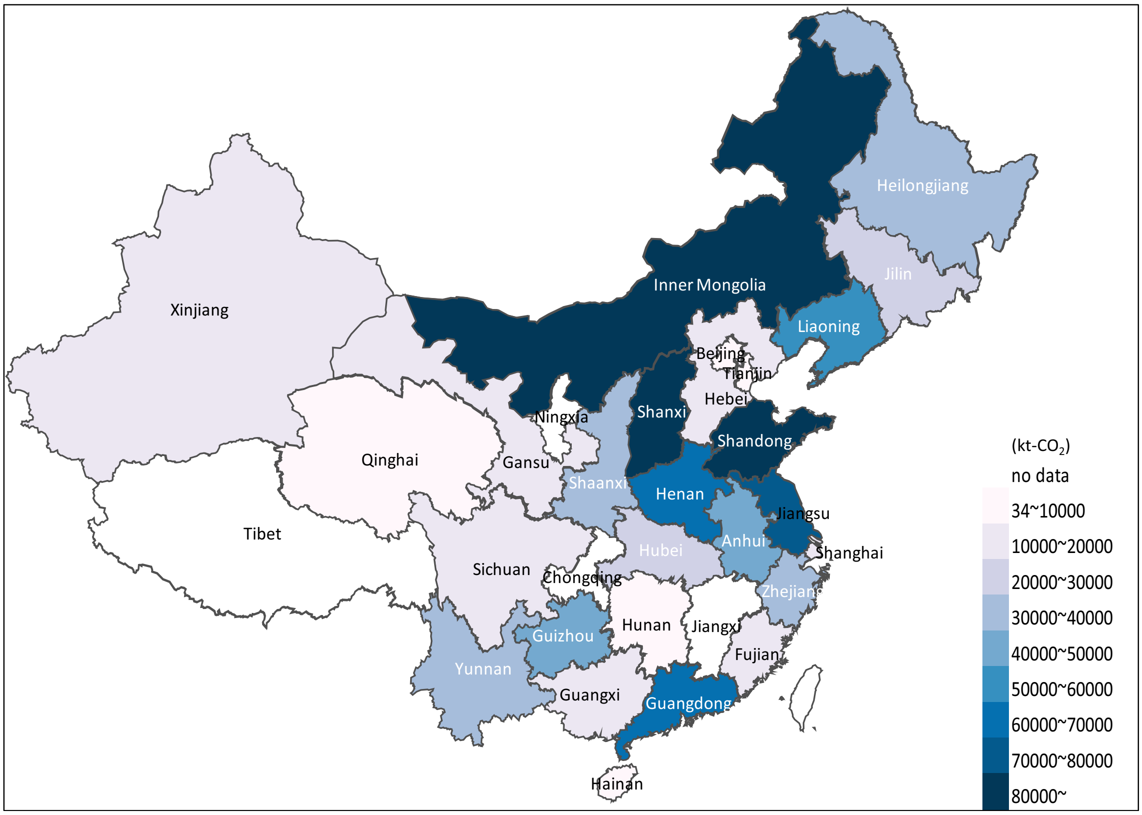


Fig. 5 Total CO_2 emissions reduction potential in each province

or more; *MEDIUM* includes plants with installed capacities of 600 up to 1000 MW.

(5) *EAST* and *CENTRAL:* dummy variables indicting regional productivity differences. As noted earlier, the eastern region is more economically developed than China's other areas, while the central area is richer in coal resources. Lam and Shiu (2001) concluded that the provinces along the coast of China and around major coal-producing areas have high TE scores, as these provinces constituted the production frontier in their empirical study. Du and Mao (2015) also showed that the EE of the eastern region is higher, whereas that of the western region is lower. Following Du and Mao (2015), our study adopts two dummy variables—*EAST* and *CENTRAL*—in order to test whether these variables have a significant impact on the CHP and thermal power plants.

The Tobit regression models for the CHP and thermal power plants are

$$\tau_k = \begin{cases} 1, & \tau_k^* \geq 1 \\ \tau_k^* = \boldsymbol{\beta}'\boldsymbol{x}_k + \varepsilon_k, & 0 < \tau_k^* < 1 \\ 0, & \tau_k^* \leq 0 \end{cases} \tag{5}$$

where τ_k is the TE of power plant k, $\boldsymbol{\beta}$ is the parameter vector estimated endogenously, $\boldsymbol{x}_k$ is the set of independent variables (i.e., *HOUR*, *LOAD*, *FUEL*, *LARGE*, *MEDIUM*, *EAST*, and *CENTRAL*) for power plant k, and ε_k is the error term, with $\varepsilon_k \sim N(0, \sigma^2)$. The parameter vector $\boldsymbol{\beta}$ is estimated using maximum likelihood estimation (MLE) (see, e.g., Greene 2002).

Table 5 gives the summary statistics for the five independent variables in our Tobit regression models. *LOAD* factors of 1 or more are due to the fact the capacity data in our cross-sectional dataset represent the capacity installed at the beginning of the period for each plant. That is, the load factor may be 1 or more as a result of a capacity increase from the beginning to the end of the period. We recognize this as one of the limitations of our research. In addition, a previous study had conducted a regression analysis of efficiency score values using dependent variables related to power plant ownership, vintage, and the existence of subsidies (see Table 1). However, this information was not available in our dataset, which is another limitation of our study.

The results of our second-stage Tobit regression analysis are reported in Table 6. Both the *HOUR* and *LOAD* factors are shown to have a positive effect on the TE score of the power plants in both models, which is nearly the same trend as in the 1995-2000 period observed in the provincial-level studies by Lam and Shiu (2001) and Lam and Shiu (2004). In particular, the *HOUR* and *LOAD* factors were shown to be more influential on TE in the CHP model than in the thermal model. This is due to the fact that the annual operating rate and annual load rate of CHP plants are relatively lower than those of thermal plants, and the variance of the two variables for the CHP plants is higher (see Table 5). A comparison of the CHP plants and thermal plants revealed that increasing the annual operating rate and annual load rate is particularly effective for improving the TE score of CHP plants.

These two factors were shown to have a significant effect on the TE score in both this study and in previous studies by Lam and Shiu (2001, 2004), primarily because the power supply and demand structure in China during the period 1995–2000, the period covered by Lam and Shiu (2001) and Lam and Shiu (2004), is quite similar to the 2011 power supply and demand structure in China addressed in this study. According to the data from IEA statistics (2020), the annual growth rate of per capita electricity consumption in China slowed in the latter half of the 1990s and the latter half of the 2000s, especially in 1997 and 2011, when the rates were only 1.04% and 1.12%, respectively. The sluggish demand for electricity during these two periods caused excess capacity in the entire Chinese power industry. As a result, the two factors (*HOUR* and *LOAD*) were the main determinants of technological efficiency during both periods.

Although the *FUEL* factor had a statistically significant effect on TE, it did not have a greater effect on TE than the *HOUR* and *LOAD* factors. This result is consistent with the results of the provincial-level empirical studies by Lam and Shiu (2001) and Lam and Shiu (2004). Furthermore, this trend was common to both the CHP and thermal models. The coefficients of the *LARGE* and *MEDIUM* factors for both the CHP and thermal models indicate that power plants with larger installed capacity tend to have higher TE scores. However, the impact of these two variables was considerably less than expected, especially in the thermal model, where the *MEDIUM* factor was not statistically significant.

Most unexpectedly, the regional dummy variable in the CHP model had no statistically significant effect. In other words, there were no regional TE differences for the CHP power plants in China. On the other hand, in the thermal model, the regional dummy variable is statistically significant, although it does not have a substantial influence on TE. This is consistent with the empirical results presented in Du and Mao (2015). These results confirm the existence of technical heterogeneity between the CHP and thermal power plants in China and support the importance of evaluating these two types of power plants separately in efficiency analysis.

Conclusion and policy implications

We evaluated the TE of 1270 Chinese power plants, distinguishing between CHP and thermal plants, using the DEA framework. The average TE value in the CHP model was found to be 0.57. In the thermal model, the average was 0.58. These values indicate that the 727 CHP power plants and 543 thermal power plants included in the study have the potential to reduce inputs, including coal input, by 43% and 42%, respectively, while maintaining current power production. Notably, in the CHP model, the WEST area had the highest TE score (0.68), followed by the CENTRAL area (0.60) and the EAST area (0.56), a result that differs from the empirical results reported in Lam and Shiu (2001). Thus, the general conclusion from these earlier studies—that power plants located in the EAST and CENTRAL regions have higher TE scores—does not hold for the case of CHP power plants.

We also estimated the CO_2 emissions reduction potential of each type of plant based on the TE scores obtained by the DEA. If the technical efficiencies of all the technically inefficient power plants improved to an achievable level, it is possible to reduce emissions by an average of 178.25 (kt-CO_2) in the CHP plants and 1516.14 (kt-CO_2) in the thermal plants. Thus, on average, the thermal power plants appear to have a greater potential to reduce CO_2 emissions relative to the potential of the CHP plants. The estimated total CO_2 emissions reduction potential of the 1270 plants treated in this study is 953 Mt-CO_2, which would account for approximately 19% of total CO_2 emissions from China's electricity and heat production sector in 2011 (International Energy Agency 2020). These results indicate that China's coal-fired power plants have significant potential to mitigate CO_2 emissions through technological improvement.

Second-stage Tobit regression analysis was used to identify the determinants of TE in China's coal-fired power plants. It was found that *HOUR* (the annual operation rate) and *LOAD* (the capacity utilization rate) have the most influence on a plant's TE score. The *FUEL*, *LARGE*, and *MEDIUM* factors have a lesser effect. The regional dummy variable in the CHP model was not statistically significant, suggesting that there are no regional TE differences among the CHP power plants in China. The fact that this result is inconsistent with the empirical results reported in Du and Mao (2015) highlights the importance of evaluating the two types of power plants (i.e., CHP power plants and thermal power plants) separately when analyzing efficiency.

This study has several important policy implications. As a general recommendation, we propose that the Chinese government seek to mitigate the CO_2 emissions derived from the country's coal-fired power plants through technological improvement. In formulating an appropriate policy, the government should first prioritize the introduction of technological improvements in power plants located in areas rich in coal resources and decreasing the amount of coal consumption at these plants. The two-step framework adopted in this study should help identify the key factors in making such improvements. Specifically, the plant manager can effectively improve the efficiency of power generation through the use of clean coal technologies such as coal washing and by reconsidering the use of boilers, turbines, and lighting equipment (Eguchi et al. 2021). In addition, importing clean coal and coal liquefaction technologies from countries such as Japan, which has the world's highest level of coal-fired power generation technology, could be effective in improving the technical efficiency of coal-fired power plants (International Energy Agency Clean Coal Centre (IEACCC) 2016). Next, in areas where coal resources are scarce, the government should reduce generation capacity, maintaining only the minimum capacity required. In actuality, the Chinese government is currently advocating a "promoting large and closing small" policy to regulate excess coal-fired power generation capacity (Zhang et al. 2014). Such a policy should be aggressively implemented, especially in areas where coal resources are scarce. In the formulation of such policy, the DEA framework methodology used in this study to assess the relative TE of power plants would provide a useful criterion when deciding which power plants to close. Finally, the Chinese government should promote the current "West-East Electricity Transmission Project" (i.e., producing electricity in coal-producing areas and transmitting the generated electricity to urban areas) to broaden the infrastructure of power distribution. Fully implementing these three proposals would produce a power distribution structure that generates electricity using technologically efficient equipment in areas rich in coal resources and distributes it to other areas of the country. In this way, it may be possible to achieve the effective mitigation of CO_2 emissions derived from China's coal-fired power plants through technological improvements.

As mentioned in the "Data" section, we were not able to identify the type of coal consumed by each power plant. Therefore, we decided not to consider CO_2 emissions as an undesirable output in our DEA framework and the environmental efficiency of each power plant was not estimated in our study. This limitation could be overcome by combining the input-output data used in this study (i.e., China Electricity Council (2015)) with the CO_2 emissions data (e.g., Tong et al. (2018)), which considers the quality of coal for each power plant. This is the future work for this study.

Appendix

Table 7 The 33 most efficient CHP power plants in China

Region	Province and municipality	Plant name
EAST	Beijing	Beijing Huaneng Thermal Power Co. Ltd.
EAST	Guangdong	Guangdong Hengyun D Power Plants
EAST	Jiangsu	Changshu No.13 Thermal Power Plant
EAST	Jiangsu	Huafang Thermal Power Plant
EAST	Jiangsu	Jiangyin Garden Thermal Power Plant (Shenghui)
EAST	Jiangsu	Jiangyin Kainuoke Thermal Power Plant (Hailan Group)
EAST	Jiangsu	Jiangyin Shuangliang Technology of Thermal Power Plant
EAST	Jiangsu	Lianyungang Tian Shen Thermal Power Co., Ltd.
EAST	Jiangsu	Nanjing Huarun Thermal Power Co., Ltd.
EAST	Jiangsu	Suzhou Huilong Thermal Power Co., Ltd.
EAST	Jiangsu	Thermal Power Plant in Suzhou Zixing Paper Company
EAST	Shandong	Shandong Chenguang Power Plant
EAST	Shandong	Shandong Jinan Shengquan Group Co., Ltd., Thermal Power Plant
EAST	Shandong	Shandong Jinhui Paper Co., Ltd. Thermal Power Plant Unit (Public)
EAST	Shandong	Shandong Laiwu Tagang Thermoelectric
EAST	Shandong	Shandong Qilu Petrochemical Company Thermal Power Plant
EAST	Shandong	Shandong Quelin Power Plant (Laiwu Taishan Sunshine)
EAST	Shandong	Shandong Taiyang Paper Thermal Power Plant # 4
EAST	Shandong	Shandong Zibo Jiaozhuang Power Plant
EAST	Shandong	Shandong Zibo Linzi Power Plant
EAST	Shanghai	Wujing Thermal Power Plant
EAST	Tianjin	Thermal Power Company of Tianjin Changluhaijing Group Co. Ltd.
EAST	Tianjin	Tianjin Huaneng Yangliu Thermal Power Co. Ltd.

Table 7 (continued)

Region	Province and municipality	Plant name
EAST	Zhejiang	Zhejiang Tianma Thermal Power Co., Ltd.
EAST	Zhejiang	Zhejiang Shangyu Hangxie Thermal Power Co., Ltd.
EAST	Zhejiang	Zhejiang Hongshan Thermoelectricity Company
CENTRAL	Anhui	Anhui Masteel Tangcha Thermal Power Plant
CENTRAL	Anhui	Anhui Masteel Thermal Power Plant
CENTRAL	Henan	Henan Mianshan Power Plant
CENTRAL	Jilin	Jilin Guodian Jiangnan Thermoelectric Co., Ltd.
CENTRAL	Jilin	Jilin Oilfield Power Plant
CENTRAL	Shanxi	Shanxi Taiyuan Second Thermal Power Plant
WEST	Gansu	Gansu Jiayuguan Hongsheng Electric Co., Ltd.

Table 8 The 18 most efficient thermal power plants in China

Region	Province and municipality	Plant name
EAST	Jiangsu	Huaneng Nanjing Jinling Power Generation Co., Ltd. (Coal)
EAST	Jiangsu	Jiangyin Ligang Power Generation Co., Ltd.
EAST	Liaoning	Liaoning Wukuang Yingkou Zhongban Plant
EAST	Liaoning	Liaoning Yingkou Angang Bayujuan Power Plants
EAST	Shandong	Shandong Donga Jinhua Power Plant
EAST	Zhejiang	Zhejiang Guodian Beilun Third Power Generation Co., Ltd.
EAST	Zhejiang	Zhejiang Huaneng Yuhuan Power Plant
EAST	Zhejiang	Zhejiang Lanxi Xiexin Environmental Thermal Power Co., Ltd.
EAST	Zhejiang	Zhejiang Ningbo Zhengyuan Electric Power Company
CENTRAL	Anhui	Anhui Chuzhou Power Plant
CENTRAL	Jiangxi	Anyuan Power Plant of Jiangxi Anyuan Industry Co. Ltd.
CENTRAL	Henan	Henan Huayang Power Plant Phase Ii
CENTRAL	Hunan	Hunan Huadian Changsha Power Generation Co., Ltd.
CENTRAL	Hunan	Hunan Huaneng Yueyang Power Generation Co., Ltd.
CENTRAL	Hunan	Hunan Huarun Power Liyujiang Co., Ltd.
CENTRAL	Inner Mongolia	Inner Mongolia Datang Togtoh Power Generation Company
CENTRAL	Shanxi	Shanxi Jingle Power Plant
CENTRAL	Shanxi	Shanxi Quwo Welfare Power Plant

Table 9 The 10 CHP power plants with the highest CO_2 emissions reduction potential

Rank	Region	Province and municipality	Plant name	Technical efficiency	CO_2 reduction potentials (kt-CO_2)
1	EAST	Liaoning	Liaoning Fuxin Jinshan Coal Thermal Power Co., Ltd.	0.60	2759.27
2	EAST	Shandong	Shandong Binzhou Weiqiao Woollen Textile Group Thermal Power Plant	0.32	1989.05
3	CENTRAL	Jilin	Jilin Longtan Power Station	0.69	1902.70
4	CENTRAL	Inner Mongolia	Inner Mongolia Baotou First Power (North Company)	0.65	1758.79
5	CENTRAL	Inner Mongolia	Inner Mongolia Hohhot Thermal Power Plant (North)	0.65	1576.01
6	EAST	Liaoning	Liaoning Shenmei Hongyang Thermal Power Co., Ltd.	0.59	1537.07
7	CENTRAL	Heilongjiang	Heilongjiang Oil Field Thermal Power Plant	0.72	1494.26
8	CENTRAL	Shanxi	Shanxi Datang Yungang Thermal Power Co., Ltd.	0.82	1477.65
9	EAST	Shandong	Shandong Tengzhou Xinyuan Thermoelectricity	0.79	1402.59
10	CENTRAL	Jilin	Jilin Changchun Third Thermoelectric Factory	0.66	1393.05

Table 10 The 10 thermal power plants with the highest CO_2 emissions reduction potential

Rank	Region	Province and municipality	Plant name	Technical efficiency	CO_2 reduction potentials (kt-CO_2)
1	CENTRAL	Inner Mongolia	Inner Mongolia Huolinhe Hong Jun Aluminum Electric Company	0.40	7867.88
2	CENTRAL	Inner Mongolia	Inner Mongolia Dalate Power Company (North)	0.55	7299.86
3	EAST	Liaoning	Liaoning Tieling Power Plant	0.52	6988.08
4	CENTRAL	Inner Mongolia	Inner Mongolia Haidai Power Generation Company	0.61	6896.38
5	EAST	Guangdong	Guangdong Baolihua Electric Power Co., Ltd.	0.51	6796.60
6	CENTRAL	Inner Mongolia	Inner Mongolia Yuanbaoshan Power Generation Company	0.46	6601.68
7	WEST	Guizhou	Guizhou Nayong Thermal Power Plant	0.46	6405.53
8	CENTRAL	Shanxi	Shanxi Zhaoguang Power Generation Co., Ltd.	0.46	6002.50
9	CENTRAL	Heilongjiang	Heilongjiang Fulaerji Plant	0.42	5755.91
10	CENTRAL	Shanxi	Shanxi Guodian Power Datong Power Generation Co., Ltd.	0.64	5381.29

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-021-14394-4.

Acknowledgements We are grateful to the editor and anonymous referees for their helpful comments and suggestions. We accept full responsibility for any errors in the manuscript.

Author contribution Tomoaki Nakaishi: conceptualization; formal analysis; investigation; methodology; project administration; software; validation; visualization; writing—original draft; writing—review & editing. Shigemi Kagawa: conceptualization; funding acquisition; formal analysis; investigation; methodology; software; validation; writing—original draft; writing—review & editing. Hirotaka Takayabu: conceptualization; formal analysis; investigation; methodology; software; validation; writing—original draft; writing—review & editing. Chen Lin: data curation; resources; validation; writing—review & editing.

Funding This research was supported by JSPS KAKENHI Grant Number JP20H00081.

Data availability The data were digitized by the authors from 2014 Power Industry Statistics. The dataset is not free and not available online.

Declarations

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Not applicable.

Conflict of interest The authors declare no competing interests.

References

Banker RD, Charnes A, Cooper WW (1984) Some models for estimating technical and scale inefficiencies in data envelopment analysis. Manage Sci 30:1078–1092

Bi GB, Song W, Zhou P, Liang L (2014) Does environmental regulation affect energy efficiency in China's thermal power generation∝ Empirical evidence from a slacks-based DEA model. Energy Policy 66:537–546

Central Compilation & Translation Press in China (2016) The 13th Five-Year Plan for economic and social development of the People's Republic of China (2016–2012). http://en.ndrc.gov.cn/newsrelease/201612/P020161207645765233498.pdf. Accessed 16 May 2021

Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2:429–444

China Electricity Council (2015) 2014 Statistical data compilation of the electric power industry. SDX Joint Publishing Company

China Electricity Yearbook committee (2012) China Electricity Yearbook 2011. China Statistics Press, Beijing

China Electricity Yearbook committee (2018) China Electricity Yearbook 2017. China Statistics Press, Beijing

Chung YH, Färe R, Grosskopf S (1997) Productivity and undesirable outputs: A directional distance function approach. J Environ Manag 51:229–240

Cook, WD, Zhu J (2013) Data Envelopment Analysis: Balanced Benchmarking

Du L, Mao J (2015) Estimating the environmental efficiency and marginal CO_2 abatement cost of coal-fired power plants in China. Energy Policy 85:347–356

Du L, Hanley A, Zhang N (2016) Environmental technical efficiency, technology gap and shadow price of coal-fuelled power plants in China: A parametric meta-frontier analysis. Resour. Energy Econ. 43:14–32

Duan N, Guo JP, Xie BC (2016) Is there a difference between the energy and CO_2 emission performance for China's thermal power industry? A bootstrapped directional distance function approach. Appl Energy 162:1552–1563

Eguchi S, Kagawa S, Okamoto S (2015) Environmental and economic performance of a biodiesel plant using waste cooking oil. J Clean Prod 101:245–250

Eguchi S, Takayabu H, Lin C (2021) Sources of inefficient power generation by coal-fired thermal power plants in China: A metafrontier DEA decomposition approach. Renew Sustain Energy Rev 138: 110562

Fukuyama H, Yoshida Y, Managi S (2011) Modal choice between air and rail: a social efficiency benchmarking analysis that considers CO_2 emissions. Environmental Economics and Policy Studies 89:89–102

Greene WH (2002) ECONOMETRICS ANALYSIS FIFTH EDITION. Prentice Hall

Horii N (2007) China Industrial Handbook 2007-2008 Edition, Chapter 4 Electric Power Industry (In Japanese)

Hu J, Wang S (2006) Total-factor energy efficiency of regions in China. Energy Policy 34:3206–3217

International Energy Agency (2020) Data and statistics (https://www.iea.org/data-and-statistics?country=WORLD&fuel=Energy%20supply&indicator=TPESbySource, accessed 10.21.20).

International Energy Agency Clean Coal Centre (IEACCC) (2016) An overview of HELE technology deployment in the coal power plant fleets of China, EU, Japan and USA. (https://www.iea-coal.org/an-overview-of-hele-technology-deployment-in-the-coal-power-plant-fleets-of-china-eu-japan-and-usa-ccc-273/, accessed 04.29.21)

IPCC (2006) IPCC Guidelines for national greenhouse gas inventories, Institute for Global Environmental Strategies (IGES)

Kaneko S, Fujii H, Sawazu N, Fujikura R (2010) Financial allocation strategy for the regional pollution abatement cost of reducing sulfur dioxide emissions in the thermal power sector in China. Energy Policy 38:2131–2141

Lam P, Shiu A (2001) A data envelopment analysis of the efficiency of China's thermal power generation. Util. Policy 10:75–83

Lam P, Shiu A (2004) Efficiency and Productivity of China's Thermal Power Generation. Int J Ind Organ 24:75–83

Lin B, Yang L (2014) Efficiency effect of changing investment structure on China's power industry. Renew Sustain Energy Rev 39:403–411

Liu CH, Lin SJ, Lewis C (2010) Evaluation of thermal power plant operational performance in Taiwan by data envelopment analysis. Energy Policy 38:1049–1058

Long X, Zhao X, Cheng F (2015) The comparison analysis of total factor productivity and eco-efficiency in China's cement manufactures. Energy Policy 81:61–66

Long X, Sun M, Cheng F, Zhang J (2017) Convergence analysis of eco-efficiency of China's cement manufacturers through unit root test of panel data. Energy 134:709–717

Long X, Chen B, Park B (2018a) Effect of 2008's Beijing Olympic Games on environmental efficiency of 268 China's cities. J Clean Prod 172:1423–1432

Long X, Wu C, Zhang J, Zhang J (2018b) Environmental efficiency for 192 thermal power plants in the Yangtze River Delta considering heterogeneity: A metafrontier directional slacks-based measure approach. Renew Sustain Energy Rev 82:3962–3971

Nakaishi T (2021) Developing effective CO2 and SO2 mitigation strategy based on marginal abatement costs of coal-fired power plants in China. Appl Energy 294:116978. https://doi.org/10.1016/j.apenergy.2021.116978

O'Donnell CJ, Rao DSP, Battese GE (2008) Metafrontier frameworks for the study of firm-level efficiencies and technology ratios. Empirical Econ 34:231–255

Shan Y, Guan D, Zheng H, Ou J, Li Y, Meng J et al (2018) Data Descriptor: China CO2 emission accounts. Sci Data 5:170201

Song C, Li M, Zhang F, He YL, Tao WQ (2015) A data envelopment analysis for energy efficiency of coal-fired power units in China. Energy Convers Manag 102:121–130

Sun C, Liu X, Li A (2018) Measuring unified efficiency of Chinese fossil fuel power plants: Intermediate approach combined with group heterogeneity and window analysis. Energy Policy 123:8–18

Takayabu H (2020) CO2 mitigation potentials in manufacturing sectors of 26 countries. Energy Econ 86:104634

Takayabu H, Kagawa S, Fujii H et al (2019) Impacts of productive efficiency improvement in the global metal industry on CO2 emissions. J Environ Manage 248:109261

Thakur T, Deshmukh SG, Kaushik SC (2006) Efficiency evaluation of the state owned electric utilities in India. Energy Policy 34:2788–2804

Tong D, Zhang Q, Davis SJ et al (2018) Targeted emission reductions from global super-polluting power plant units. Nat Sustain 1:59–68

Tsutsui M (2001) Analysis of the efficiency taking into account the environmental performance of electrical industry: application of DEA. Central Res. Inst. Electr. Power Ind. Rep Y00017:1–12 (in Japanese)

Wang C, Cao X, Mao J, Qin P (2019) The changes in coal intensity of electricity generation in Chinese coal-fired power plants. Energy Econ 80:491–501

Wei X, Zhang N (2020) The shadow prices of CO_2 and SO_2 for Chinese Coal-fired Power Plants: A partial frontier approach. Energy Econ 85:104576

Wei C, Löschel A, Liu B (2013) An empirical analysis of the CO_2 shadow price in Chinese thermal power enterprises. Energy Econ 40:22–31

Wu C, Oh K, Long X, Zhang J (2019) Effect of installed capacity size on environmental efficiency across 528 thermal power stations in North China. Environ Sci Pollut Res 26:29822–29833

Yan D, Lei Y, Li L, Song W (2017) Carbon emission efficiency and spatial clustering analyses in China's thermal power industry: Evidence from the provincial level. J Clean Prod 156:518–527

Yang H, Pollitt M (2009) Incorporating both undesirable outputs and uncontrollable variables into DEA: The performance of Chinese coal-fired power plants. Eur J Oper Res 197:1095–1105

Yang H, Pollitt M (2010) The necessity of distinguishing weak and strong disposability among undesirable outputs in DEA: Environmental

performance of Chinese coal-fired power plants. Energy Policy 38: 4440–4444
Zhang N, Kong F, Choi Y, Zhou P (2014) The effect of size-control policy on unified energy and carbon efficiency for Chinese fossil fuel power plants. Energy Policy 70:193–200
Zhao X, Ma C (2013) Deregulation, vertical unbundling and the performance of China's large coal-fired power plants. Energy Econ 40: 474–483
Zhou P, Ang BW, Wang H (2012) Energy and CO_2 emission performance in electricity generation: A non-radial directional distance function approach. Eur J Oper Res 221:625–635
Zhou Y, Xing X, Fang K, Liang D, Xu C (2013) Environmental efficiency analysis of power industry in China based on an entropy SBM model. Energy Policy 57:68–75