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Energy-Related CO₂ Emission in China's Provincial Thermal Electricity Generation: Driving Factors and Possibilities for Abatement

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Abstract: China's electricity sector mainly relies on coal-fired thermal generation, thus resulting that nearly 50% of China's total CO₂ emissions coming from the electricity sector. This study focuses on the provincial CO₂ emissions from China's thermal electricity generation. Methodologically, Index Decomposition Analysis (IDA), facilitated by the Shapley Index, is applied to discover the driving factors behind CO₂ emission changes at the provincial level. In addition, the Slack-based Model (SBM) is used to identify which provincial power grids should be allocated with a higher (lower) CO₂ reduction burden. The IDA results indicate that economic activity pushed the CO₂ emissions up in all 30 provincial power grids, excluding Beijing and Shanghai; the carbon factor contributed to a decrease in the CO₂ emissions in all 30 provincial power grids, with the exception of Jilin, Guangdong, and Ningxia; though the effect of energy intensity varied across the 30 provinces, it played a significant role in the mitigation of CO₂ emissions in Beijing, Heilongjiang, Liaoning, Jilin, Shanghai, Anhui, and Sichuan. According to the SBM results, the lowest carbon shadow prices are observed in Yunnan, Shanghai, Inner Mongolia, Jilin, Qinghai, Guizhou, Anhui, and Ningxia. These provincial power grids, thus, should face higher mitigation targets for CO₂ emissions from thermal electricity generation.

Keywords: CO₂ emissions; index decomposition analysis; shadow prices; environmental efficiency

1. Introduction

There is a global consensus that climate change is becoming a serious issue to be addressed in the 21st century [1,2]. In terms of the Fifth Assessment Report published by the Intergovernmental Panel on Climate Change (IPCC), CO₂ emission is considered as the most important cause of climate change, and the global concentration of CO₂ reached a record high in 2014. As for China, since its 'Reform and Opening-up' program initiated in the late 1970s, China's economy has enjoyed a long-term rapid development which has resulted in a gradual upward trend in CO₂ emissions. Though China had signed the Kyoto Protocol, China surpassed the United States and became the largest CO₂ emitter in the world in 2006 [3]. The International Energy Agency estimated that China's CO₂ emissions will exceed 11 billion tons in 2030 if no indispensable reduction measures are taken. The United Nations Framework Convention on Climate Conference in 2015 concluded with a commitment by the Chinese government that China's CO₂ emission would peak around 2030 and the carbon intensity would be reduced by 60–65% in 2030 compared to 2005. Furthermore, during the 13th Five-Year Plan period

(2015–2020), the Chinese government announced that the country would decrease its CO₂ emission intensity (measured per unit of Gross Domestic Product (GDP)) by 18% between 2015 and 2020.

Noteworthy, coal dominates China's energy resource endowments, thus determining the energy-mix for China's electricity generation. Thermal power generation remains the major source in spite of the decline in the proportion of thermal electricity generation from 82.3% in 2006 down to 73.7% in 2015 (see Figure 1). This may suggest that although the Chinese government has stimulated the development of renewable energy (e.g., solar power, nuclear power, wind power) in recent years, thermal electricity generation still represents a large proportion of total electricity at present [4,5], which implies generating substantial CO₂ emissions.

Figure 1. The share of thermal electricity generation in the total electricity in China. * Data source: the website of National Bureau of Statistics of the People's Republic of China.

Therefore, the major contribution by thermal electricity generation to China's total CO₂ emission, as well as China's pledge to cut its carbon intensity, imply there is considerable pressure on the thermal electricity generation sector to identify the most effective CO₂ emission mitigation policies. To reduce the CO₂ emission arising from thermal power generation, it is important to investigate into the driving forces behind the emission. Structural Decomposition Analysis (SDA) and IDA are two major methods to analyze the changes in CO₂ emissions with multiple driving factors. The major difference is that SDA uses information from input-output tables [6–8], whereas IDA requires no information about inter-sectoral linkages. Su and Ang [7] conducted a literature review on SDA in the application field of energy and carbon emissions during 1999–2010, and Wang et al. [9] summarized related SDA studies published during 2010–2015. Though SDA can facilitate a more detailed decomposition analysis involving the interlinkages among the sectors of the economy, the availability of the input-output tables is the limiting factor for applying SDA [7,10]. Therefore, IDA has been widely applied for analysis of CO₂ emissions in different scopes, e.g., international [11–13], national [14–16], sub-national [17–19], or a single sector of the economy [20–22]. Index theory is usually applied to establish particular models for IDA. In view of the underlying difference in the index techniques, IDA can be divided into two main classes: IDA with the Divisia Index and IDA with the Laspeyres Index [23].

Shapley/Sun value, a strand of the Laspeyres-based index, was first applied in IDA by Sun [24] and Albrecht et al. [25]. Later on, Ang et al. [26] named the method as the Shapley/Sun Index. The Shapley/Sun Index has an obvious advantage that it does not suffer from path dependency, i.e., the results obtained do not depend on the ordering of factors [27]. The Shapley/Sun Index has been widely used in the analysis of CO₂ emission patterns and proved to be effective. For instance, Li et al. [28] analyzed the major drivers behind energy-related CO₂ emissions arising from agriculture in European countries based on the Shapley/Sun Index. Yu et al. [29] applied the Shapley/Sun Index decomposition to allocate the CO₂ emission reduction targets in China at the provincial level. Zhang et al. [30] employed the Shapley value method to identify the regional allocation of carbon emission quotas in China. Alves and Moutinho [31] applied the Sun Index to analyze the factors which

influence the changes in CO₂ emission intensity in Portugal at the sectoral level. However, no study has employed the Shapley/Sun Index to analyze CO₂ emissions in China's thermal electricity sector so far. From an empirical viewpoint, this paper seeks to use this particular technique for IDA to reveal the impacts of different factors on CO₂ emission changes in China's thermal electricity generation.

Another point worth noting, considering China's thermal electricity generation, is that the extant literature has not identified which provincial power grids should face higher or lower carbon dioxide reduction targets. Indeed, the directions for reductions can be defined by means of environmental efficiency and shadow price estimates. From a cost-efficiency perspective, provincial power grids with relatively lower marginal abatement costs are supposed to undertake a higher emission reduction burden [32,33]. In this regard, environmental efficiency measures [34,35] are useful for they cannot only identify the improvement for key factors, but also take non-marketable outputs (e.g., CO₂ emission) into consideration. Data Envelopment Analysis (DEA) provides a non-parametric approach towards the estimation of environmentally-sensitive production frontiers and distance functions [36]. Among the environmental efficiency measures, SBM proposed by Cooper et al. [37] considers non-oriented movement towards production frontier. This property is particularly attractive as this paper focuses on the reduction on CO₂ emission along with possible increases in desirable output without a priori assumptions on the underlying trade-offs. Wei et al. [38] and Li et al. [28] applied SBM to the analysis of CO₂ emission reduction in China and the European Union's agriculture sector, respectively. This research, therefore, utilizes a non-directional, non-radial, and non-parametric model based on SBM for the analysis of environmental efficiency and the shadow prices of CO₂ emission in China's thermal electricity at the province level.

Furthermore, IDA and environmental analysis have seldom been utilized in an incorporate manner, even though the efficiency analysis method (e.g., SBM) can refine the directions for reductions in CO₂ emission. So far, to the best of knowledge, only Li et al. [28] applied IDA and efficiency analysis jointly to derive the driving forces of CO₂ emission and to discover the possibilities for CO₂ emission abatement in the European Union agriculture sector. Methodologically, this paper could be regarded as the first paper to analyze the CO₂ emission from China's electricity generation, specifically China's thermal electricity generation, with the integrated manner containing both the IDA and environmental efficiency methods.

2. Literature Review on China's Thermal Electricity Generation

Although different types of electricity generation are present in China, some papers did not consider separate sources of energy and treated the electricity generation sector as a whole when analyzing the driving forces of CO₂ emissions in this sector [39–43]. This can be partly explained by the fact that the structure of the Chinese electricity generation sector had been rather simple prior to the expansion of the renewables. Given that coal-fired thermal electricity generation plays a dominant part in China's CO₂ emission reduction, Zhou et al. [44] and Yan et al. [45] applied IDA to examine the CO₂ emissions from thermal electricity generation in China. To the best of our knowledge, these two are the only papers related to the decomposition analysis of CO₂ emissions in China's thermal electricity generation, but both of them are at the regional level. Indeed, China's provinces are rather different in their levels of economic development, generated energy (see Figure 2), and resource endowments [46,47]. As China's CO₂ emission mitigation measures and policies are quite diverse at the province level, the driving forces of CO₂ emissions may also vary across provinces. In this regards, the decomposition analysis of provincial CO₂ emissions will not only provide targeted policy implications for China's central government and local policy-makers, but also strengthen international readers' apprehension of China's CO₂ emissions and their driving forces. Given these benefits, Liu et al. [48], Xu et al. [49], Ma [50], and Wang et al. [51] have examined the driving forces behind the changes of China's energy-related CO₂ emissions/energy consumption at the province level.

Figure 2. Distribution of GDP per capita and generated electricity per capita of China's 30 provinces in 2015. * Data source: the website of National Bureau of Statistics of the People's Republic of China.

In regard to environmental performance analysis and marginal abatement cost of CO₂ emission reduction in electricity generation, there have been several studies on different countries and regions [52–55]. Some previous studies [56–58] examined the environmental efficiency of the thermal electricity sector in China based on provincial data. Still, to the best of our knowledge, there has been no research on China's thermal electricity generation carried out to derive the shadow prices of CO₂ emissions at the province level. Though some studies have focused on shadow prices of CO₂ emissions in China's thermal electricity generation, they are all at the plant-level. The related studies include those by Wei et al. [33], Zhang and Choi [59], Du and Miao [4], Yu et al. [60], among others. Noteworthy, according to the seven pilot regional carbon trading markets (i.e., Beijing, Tianjin, Shanghai, Guangdong, Shenzhen, Hubei, and Chongqing) launched by the Chinese government in 2013, different provinces have different carbon market prices at the earlier stages of carbon trading construction in China. Thus, there is a need for the province-level shadow price analysis in China's thermal electricity sector to derive the marginal abatement cost of provincial CO₂ emissions, as well as to measure whether the emission trading is worthwhile. Additionally, to fulfill China's carbon reduction promise, there is a “national target—provincial target” distribution mode in China, which can allocate the carbon reduction burden from top to bottom. In this point, shadow prices can also contribute to identifying which province should shoulder more (less) CO₂ emission reduction burden in thermal electricity sector from a cost-efficiency perspective [32,33].

The rest of this paper is arranged as follows: Section 3 presents the techniques employed for the analysis; Section 4 portrays the trends in the CO₂ emissions and brings forward the results of IDA for China's thermal electricity sector at the provincial level; Section 5 discusses the trends in environmental efficiency and shadow prices of CO₂ emissions in this sector for each provincial electricity power grid; and Section 6 proposes the conclusions.

3. Methodology

In this section, we will outline the main techniques applied in this research, i.e., the calculation of CO₂ emissions, the Shapley/Sun Index, and the Slack-based DEA model.

3.1. Calculation of CO₂ Emissions

For an easier exposition, let p represent the p -th province associated with the corresponding power grid, i represents the fuel type, and t represents the year. Following the method provided by the IPCC, the CO₂ emissions $C_{(p,t)}$ resulting from thermal electricity generation in the p -th province at year t can be calculated via:

$$C_{(p,t)} = \sum E_{pi}^t \times F_i^C \times O_i \times 44/12 \quad (1)$$

where E_{pi}^t denotes the amount of fuel type i used by the provincial power grid of province p at year t ; F_i^C denotes the carbon emission factor of fuel i (in tons of carbon per terajoule—tc/TJ); O_i denotes the carbon oxidation factor of fuel i ; 44/12 is the ratio of the molecular weight ratio of CO_2 to the atomic weight of C.

Note that energy embodied in different types of fuel is measured in different units. Therefore, let the initial variable I_{pi}^t represent the energy provided by combustion of fuel type i in province p at the t -th year, as measured in any unit of measurement. All the units of measurement are then converted into megajoules (MJ), as represented by variable E_{pi}^t . Specifically, E_{pi}^t can be calculated as $E_{pi}^t = I_{pi}^t \times V_i^{\text{fuel caloric value}}$. Meanwhile, $F_i^{\text{CO}_2} = F_i^C \times O_i \times 44/12$, where $F_i^{\text{CO}_2}$ denotes the CO_2 emission factor of fuel i (in kilogram per TJ—kg CO_2 /TJ). Therefore, we obtain the following formula:

$$\begin{aligned} C_{(p,t)} &= \sum E_{pi}^t \times F_i^{\text{CO}_2} \\ &= \sum E_{pi}^t \times F_i^C \times O_i \times 44/12 \\ &= \sum \left(I_{pi}^t \times V_i^{\text{fuel caloric value}} \right) \times F_i^C \times O_i \times 44/12 \end{aligned} \quad (2)$$

3.2. Shapley/Sun Index

Among the several factors affecting the CO_2 emissions, both Zhou et al. [44] and Yan et al. [45] have proved that economic activity, energy efficiency, and changes in the fuel-mix have the most significant influence in the case of China's thermal electricity sector. Thus, in order to deepen the research of Zhou et al. [44] and Yan et al. [45], as well as to proceed with the Shapley/Sun Index for IDA, we consider the following three factors in this study: carbon emission factor (C_F^t), energy intensity (C_I^t), and economic activity factor (C_G^t). Then the CO_2 emissions (C_t) from thermal electricity generation in year t can be decomposed as:

$$C_t = \frac{C_t}{E_t} \frac{E_t}{GDP_t} GDP_t = C_F^t C_I^t C_G^t, \quad (3)$$

where E_t represents the emission-related energy use in year t (in million-tonne coal equivalent (Mtce)), and GDP_t represents the provincial GDP in year t (in CNY billions). Obviously, $C_F^t = \frac{C_t}{E_t}$, $C_I^t = \frac{E_t}{GDP_t}$, $C_G^t = GDP_t$.

Assume that $\Delta C_F^{(t_0, t_T)}$, $\Delta C_I^{(t_0, t_T)}$, $\Delta C_G^{(t_0, t_T)}$ represent the effects associated with changes in factors C_F^t , C_I^t , and C_G^t , respectively. According to Ang et al. [26], the CO_2 emission change between the base year t_0 and target year t_T can be decomposed as defined by the following equation:

$$\begin{aligned} \Delta C_{(t_0, t_T)} &= C_{t_T} - C_{t_0} \\ &= C_F^{t_T} C_I^{t_T} C_G^{t_T} - C_F^{t_0} C_I^{t_0} C_G^{t_0} \\ &= \Delta C_F^{(t_0, t_T)} + \Delta C_I^{(t_0, t_T)} + \Delta C_G^{(t_0, t_T)}. \end{aligned} \quad (4)$$

Furthermore, the Shapley value [61] can be used to identify the effects of each factor. This study focuses on the three factors, so we have:

$$\Delta C_x = \sum_{s=1}^3 \frac{(s-1)!(3-s)!}{3!} \sum_{S: x \in S, |S|=s} (C(S) - C(S \setminus x)), \quad (5)$$

where S is the set of the aforementioned influence factors driving CO_2 emissions generated by China's thermal electricity generation, with each factor obtaining values of period T , i.e., $C(S) =$

$\prod_{C \in S} C^{t_T} \prod_{C \notin S} C^{t_0}$. Then through Equations (6)–(8), we can calculate $\Delta C_F^{(t_0, t_T)}$, $\Delta C_I^{(t_0, t_T)}$, and $\Delta C_G^{(t_0, t_T)}$ as follows:

$$\Delta C_F^{(t_0, t_T)} = \frac{1}{3}(C_F^{t_T} C_I^{t_0} C_G^{t_0} + C_F^{t_T} C_I^{t_T} C_G^{t_T} - C_F^{t_0} C_I^{t_0} C_G^{t_0} - C_F^{t_0} C_I^{t_T} C_G^{t_T}) + \frac{1}{6}(C_F^{t_T} C_I^{t_T} C_G^{t_0} + C_F^{t_T} C_I^{t_0} C_G^{t_T} - C_F^{t_0} C_I^{t_T} C_G^{t_0} - C_F^{t_0} C_I^{t_0} C_G^{t_T}) \quad (6)$$

$$\Delta C_I^{(t_0, t_T)} = \frac{1}{3}(C_I^{t_T} C_F^{t_0} C_G^{t_0} + C_I^{t_T} C_F^{t_T} C_G^{t_T} - C_I^{t_0} C_F^{t_0} C_G^{t_0} - C_I^{t_0} C_F^{t_T} C_G^{t_T}) + \frac{1}{6}(C_I^{t_T} C_F^{t_T} C_G^{t_0} + C_I^{t_T} C_F^{t_0} C_G^{t_T} - C_I^{t_0} C_F^{t_T} C_G^{t_0} - C_I^{t_0} C_F^{t_0} C_G^{t_T}) \quad (7)$$

$$\Delta C_G^{(t_0, t_T)} = \frac{1}{3}(C_G^{t_T} C_F^{t_0} C_I^{t_0} + C_G^{t_T} C_F^{t_T} C_I^{t_T} - C_G^{t_0} C_F^{t_0} C_I^{t_0} - C_G^{t_0} C_F^{t_T} C_I^{t_T}) + \frac{1}{6}(C_G^{t_T} C_F^{t_T} C_I^{t_0} + C_G^{t_T} C_F^{t_0} C_I^{t_T} - C_G^{t_0} C_F^{t_T} C_I^{t_0} - C_G^{t_0} C_F^{t_0} C_I^{t_T}) \quad (8)$$

The calculations in Equations (3)–(8) are repeated for each province and the corresponding notation of provinces is omitted.

3.3. Slack-Based Measure of Efficiency

The DEA has been extended to account for undesirable outputs in different ways [62,63]. The SBM proposed by Cooper et al. [37] can accommodate both desirable outputs and undesirable ones, e.g., CO₂ emissions [28,54]. The present study utilizes SBM to derive environmental efficiency and shadow prices of CO₂ emissions from China's thermal electricity generation.

Assuming the input, desirable output, and undesirable output for K decision-making units (DMUs) are denoted by three vectors, i.e., $x \in R^I$, $d \in R^M$, $u \in R^N$, respectively. Assuming constant-returns-to-scale technology and strong disposability of outputs, the following DEA technology is obtained:

$$V = \{(x, d, u) | x \geq X\lambda, d \leq Y\lambda, u \geq U\lambda, \lambda \geq 0\}, \quad (9)$$

where $\lambda \in R^p$ is the intensity vector, X is a $(i \times K)$ matrix of inputs, D is a $(m \times K)$ matrix of desirable outputs, U is a $(n \times K)$ matrix of undesirable outputs, and $X, D, U > 0$. Let ρ_t denote efficiency score of t ($t = t_0, t_0 + 1, \dots, t_T$) year, (x_i^t, d_m^t, u_n^t) present the t -th input-output vector. Then the extended SBM, measuring the efficiency of a certain decision making unit in terms of slacks in inputs and outputs, can be expressed as follows:

$$\rho_t = \min \frac{1 - \frac{1}{I} \sum_{i=1}^I \frac{s_i^x}{x_i^t}}{1 + \frac{1}{M+N} \left(\sum_{d=1}^M \frac{s_m^d}{d_m^t} + \sum_{u=1}^N \frac{s_n^u}{u_n^t} \right)} \quad (10)$$

$$\begin{aligned} \text{s.t. } & x_i = \lambda X + s^x, \\ & d_m = \lambda D - s^d, \\ & u_n = \lambda U + s^u, \\ & \lambda \geq 0, s^x \geq 0, s^d \geq 0, s^u \geq 0. \end{aligned} \quad (11)$$

The vectors $s^x \in R^I$, $s^d \in R^D$ and $s^u \in R^U$ denote excesses in inputs, shortages in desirable outputs, and excesses in undesirable outputs, respectively. It is worthy pointing out that $0 < \rho_t \leq 1$, and $\rho_t = 1$ represents the full efficiency. As shown below, Equation (12) is a non-linear programming model which is equivalent to Equation (11):

$$\rho_t = \min_{s_i^x, s_m^d, s_n^u} \frac{1 - \frac{1}{I} \sum_{i=1}^I \frac{s_i^x}{x_i^t}}{1 + \frac{1}{M+N} \left(\sum_{d=1}^M \frac{s_m^d}{d_m^t} + \sum_{u=1}^N \frac{s_n^u}{u_n^t} \right)} \quad (12)$$

$$s.t. \begin{cases} x_i = \sum_{i=1}^I \lambda x_i^I + s_i^x, & i = 1, 2, \dots, I, \\ d_m = \sum_{m=1}^M \lambda d_m^M + s_m^d, & m = 1, 2, \dots, M, \\ u_n = \sum_{n=1}^N \lambda d_n^N + s_n^u, & n = 1, 2, \dots, N, \\ \lambda \geq 0, s_i^x \geq 0, s_m^d \geq 0, s_n^u \geq 0. \end{cases} \quad (13)$$

Furthermore, Equation (12) can be transformed into the following linear multiplier model:

$$\delta_t = \max_{\delta, \eta_i^x, \eta_m^d, \eta_n^u} \delta \quad (14)$$

$$s.t. \begin{cases} \delta + \sum_{i=1}^I \eta_i^x x_i^t - \sum_{m=1}^M \eta_m^d d_m^t + \sum_{n=1}^N \eta_n^u u_n^t = 1, \\ \sum_{m=1}^M \eta_m^d d_m^k - \sum_{n=1}^N \eta_n^u u_n^k - \sum_{i=1}^I \eta_i^x x_i^k \leq 0, & k = 1, 2, \dots, K, \\ \eta_i^x \geq \frac{1}{I} (1/x_i^t), & i = 1, 2, \dots, I, \\ \eta_m^d \geq \frac{1}{M+N} (1/d_m^t), & m = 1, 2, \dots, M, \\ \eta_n^u \geq \frac{1}{M+N} (1/u_n^t), & n = 1, 2, \dots, N. \end{cases} \quad (15)$$

where η_i^x , η_m^d and η_n^u denote the virtual prices of inputs, desirable outputs, and undesirable outputs, respectively. Let p_j denote the market price of the j -th output. In our case, we use electricity produced by thermal electricity generation as the “numeraire” output. Following Wei et al. [33], we can then use the virtual prices yielded by the above model to count the shadow prices of undesirable output p_u via:

$$P_u = P_j \cdot \frac{\eta_n^u}{\eta_m^d} \quad (16)$$

The shadow price is the marginal abatement cost and represents the trade-off between the desirable output and undesirable output [38]. The slack-based model is implemented in General Algebraic Modeling System (GAMS) and the computations are conducted on a PC equipped with an Intel Core i5-750M CPU at 2.6 GHz, with 4 GB RAM, and Windows 8 (64bit) operating system.

4. Energy Consumption and IDA Results

4.1. Data Sources

This study focuses on thermal electricity generation in China’s 30 provinces. Due to insufficient energy data, Tibet, Hong Kong SAR, Macao SAR, and Taiwan are not included in the analysis. The research period spans the years 2000–2013. Initial data on energy consumption and provincial GDP are retrieved from issues of the China Energy Statistical Yearbook (CESY) [64] and the China Statistical Yearbook (CSY) [65], respectively. Emission-related energy use (in Mtce), provincial GDP (in CNY billion), and CO₂ emissions (in million ton—Mt) are the three absolute indicators related to CO₂ emissions. Emission-related energy use measures the energy input in thermal electricity generation; provincial GDP reflects the changes in provincial economic activity; CO₂ emissions from thermal electricity generation represent the environmental pressures.

The fuel types used in thermal electricity generation and the corresponding conversion factors used to transfer to coal equivalents are shown in Table 1. Based on Table 1 and the related data of thermal electricity generation from CESY [64], we can obtain the provincial energy use for thermal electricity generation in China. Table 2 summarizes F_i^C , O_i , $F_i^{CO_2}$, and $V_i^{fuel \text{ caloric value}}$ for each fuel type i . $V_i^{fuel \text{ caloric value}}$ is derived from CESY [64], whereas F_i^C and O_i are based on IPCC [44,66].

Table 1. Conversion factors for different fuel types from physical units to coal equivalent.

	Fuel Type	<i>i</i>	Unit	Conversion Factor
Coal	Raw coal	1	10 ⁴ tn	0.714 kg ce/kg
	Cleaned coal	2	10 ⁴ tn	0.900 kg ce/kg
	Other washed coal	3	10 ⁴ tn	0.286 kg ce/kg
	Briquettes	4	10 ⁴ tn	0.700 kg ce/kg
	Gangue	5	10 ⁴ tn	0.179 kg ce/kg
	Coke	6	10 ⁴ tn	0.971 kg ce/kg
	Other cooking products	7	10 ⁴ tn	1.500 kg ce/kg
Oil	Crude oil	8	10 ⁴ tn	1.429 kg ce/kg
	Gasoline	9	10 ⁴ tn	1.471 kg ce/kg
	Diesel oil	10	10 ⁴ tn	1.457 kg ce/kg
	Fuel oil	11	10 ⁴ tn	1.429 kg ce/kg
	Petroleum coke	12	10 ⁴ tn	1.092 kg ce/kg
	Other petroleum	13	10 ⁴ tn	1.400 kg ce/kg
Gas	Coke oven gas	14	10 ⁸ m ³	0.614 kg ce/m ³
	Blast furnace gas	15	10 ⁸ m ³	1.286 kg ce/10 ⁴ m ³
	Converter gas	16	10 ⁸ m ³	2.714 kg ce/10 ⁴ m ³
	Other gas	17	10 ⁸ m ³	0.657 kg ce/m ³
	Liquefied petroleum gas (LPG)	18	10 ⁴ tn	1.714 kg ce/kg
	Refinery gas	19	10 ⁴ tn	1.571 kg ce/kg
	Natural gas	20	10 ⁸ m ³	1.330 kg ce/m ³
	Liquefied petroleum gas (LNG)	21	10 ⁴ tn	1.757 kg ce/kg
Others	Other energy	22	10 ⁴ tce	1.000 kg ce/kg
	Heat	23	10 ¹⁰ kJ	0.034 kg ce/10 ⁶ J

Table 2. The carbon emission factor F_i^C , carbon oxidation factor O_i , CO₂ emission factor $F_i^{CO_2}$, and fuel caloric value $V_i^{fuel\ caloric\ value}$ of fuel *i*.

Fuel <i>i</i>	Unit	F_i^C (tc/TJ)	O_i (%)	$F_i^{CO_2} = F_i^C \times O_i \times 44/12 \times 10^3$ (kg CO ₂ /TJ)	$V_i^{fuel\ caloric\ value}$ (MJ/ton or MJ/m ³)
Raw coal	10 ⁴ ton	25.8	100	94,600	20,908
Cleaned coal	10 ⁴ ton	25.8	100	94,600	26,344
Other washed coal	10 ⁴ ton	25.8	100	94,600	8363
Briquettes	10 ⁴ ton	26.6	100	97,500	20,908
Gangue	10 ⁴ ton	25.8	100	94,600	8372
Coke	10 ⁴ ton	29.2	100	107,100	28,435
Other cooking	10 ⁴ ton	25.8	100	94,600	28,435
Crude oil	10 ⁴ ton	20.0	100	73,300	41,816
Gasoline	10 ⁴ ton	18.9	100	69,300	43,070
Diesel oil	10 ⁴ ton	20.2	100	74,100	42,652
Fuel oil	10 ⁴ ton	21.1	100	77,400	41,816
Petroleum coke	10 ⁴ ton	26.6	100	97,500	31,980
Other petroleum	10 ⁴ ton	20.0	100	73,300	41,816
Coke oven gas	10 ⁸ m ³	12.1	100	44,400	16,726
Blast furnace gas	10 ⁸ m ³	70.8	100	259,600	3767
Converter gas	10 ⁸ m ³	49.6	100	181,900	7953
Other gas	10 ⁸ m ³	12.1	100	44,400	5227
LPG	10 ⁴ ton	17.2	100	63,100	50,179
Refinery gas	10 ⁴ ton	15.7	100	57,600	46,055
Natural gas	10 ⁴ ton	15.3	100	56,100	38,931
LNG	10 ⁸ m ³	15.3	100	56,100	51,486

4.2. Energy Consumption and CO₂ Emissions

According to Table 1 and the initial energy use I_{pi}^t from CESY [64], $C_{(p,t)}$ can be calculated through Equation (2). The mean values of provincial GDP, relative CO₂ emissions and energy use of thermal electricity generation are given in Table 3. Noteworthy, GDP at constant prices (base year 2000) is used in this study.

Table 3. Mean values of absolute variables for the 30 provinces in China, 2000–2013.

Provinces	GDP of Province (CNY Billion in 2000 Price)	Energy Use (Mtce)	CO ₂ Emissions (Mt)
Beijing	6432	5.69	15.08
Tianjin	3462	12.85	35.32
Hebei	10,261	54.00	143.62
Shanxi	3755	54.59	147.56
Inner Mongolia	3131	72.24	199.06
Liaoning	9498	36.97	100.51
Jilin	3970	19.68	53.88
Heilongjiang	6411	25.20	68.98
Shanghai	9706	39.01	105.94
Jiangsu	17,401	75.16	204.65
Zhejiang	12,493	45.10	121.77
Anhui	5904	52.57	143.62
Fujian	7658	20.85	56.62
Jiangxi	4075	14.66	39.90
Shandong	16,961	76.05	207.10
Henan	10,279	60.34	164.46
Hubei	7212	21.11	56.17
Hunan	7225	17.95	48.03
Guangdong	21,851	63.42	167.90
Guangxi	4231	13.19	33.00
Hainan	1072	2.83	7.55
Chongqing	3643	9.13	24.15
Sichuan	7991	18.92	51.85
Guizhou	2095	25.30	69.18
Yunnan	4091	16.96	45.26
Shannxi	3670	23.34	63.83
Gansu	2142	14.64	40.32
Qinghai	536	3.03	8.38
Ningxia	600	16.53	45.70
Xinjiang	2774	16.30	44.76

We now turn to the dynamics in the CO₂ emissions from thermal electricity generation in 30 provincial power grids. Figure 3 presents the indices of CO₂ emissions and related indicators (e.g., energy use and GDP) for the whole sample of 30 provinces, from 2000–2013. Accordingly, we can know that the three absolute indicators followed an upward trend and increased more than two-fold through the years 2000–2013. Obviously, energy use was nearly in line with the CO₂ emission, yet the increase in energy use was higher than that in CO₂ emission. Particularly, the energy use increased by 228%, whereas CO₂ emission increased by 216%, which implies that though energy use has a strong influence on CO₂ emission, there are still other factors influencing the CO₂ emission.

Especially, the CO₂ emissions from thermal electricity generation in 2000 and 2013 are shown in Figure 4. It is clear that the levels and average annual growth rates (AAGRs) of CO₂ emissions varied across the 30 provincial power grids in China. In 2013, the highest levels of CO₂ emissions were observed in Inner Mongolia (370 Mt), Jiangsu (324 Mt), and Shandong (324 Mt). At the other end of the spectrum, Qinghai, Beijing, and Hainan emitted the lowest CO₂ emissions of 13 Mt, 14 Mt, and 16 Mt, respectively in 2013. The AAGRs also differed across the 30 provincial power grids. The emissions of Ningxia, Inner Mongolia, and Xinjiang showed the highest AAGRs of 17.9%, 17.44%, and 14.6%, respectively. Obviously, Shanghai and Beijing are the only two power grids that have negative growth rates of −3.29% and −0.46%. These results indicate that the latter two provincial power grids are good-performing ones in regards to emissions reduction in the thermal electricity sector.

Based on the mean values of provincial energy consumption in thermal electricity generation through years 2000–2013, the 30 provincial power grids can be divided into four categories (see Table 4 and Figure 5). Accordingly, there are five provincial power grids whose mean values of

energy consumption in thermal electricity generation exceeded 60 Mtce during 2000–2013, i.e., Henan, Guangdong, Inner Mongolia, Jiangsu and Shandong power grids. The intensive use of energy in these five provincial power grids can be attributed to the high economic growth rates and large population there. By comparison, Hainan, Qinghai, Beijing, Chongqing, Tianjin, Guangxi, Gansu, and Jiangxi power grids showed the lowest energy consumption in thermal electricity generation. According to Figure 5, it is clear that the mean values of provincial energy consumption from thermal electricity should not be analyzed by region. For example, the energy consumptions of Henan, Guangdong, and Inner Mongolia all exceed 60 Mtce, yet these provincial power grids belong to different regions. Hence, unlike the present literature, this paper looks into the CO₂ emissions from China's thermal electricity generation at the provincial level for the first time.

Figure 3. Carbon dioxide emission and related indicators for the whole 30 provinces, 2000–2013.

Figure 4. CO₂ emissions from thermal electricity generation and the related AAGRs of the 30 provincial power grids in China (2000 and 2013).

Table 4. The mean energy consumption for provincial thermal electricity generation, 2000–2013.

Mean Energy Consumption	Provinces/Provincial Power Grids
<15 Mtce	Hainan, Qinghai, Beijing, Chongqing, Tianjin, Guangxi, Gansu, Jiangxi
15–30 Mtce	Xinjiang, Ningxia, Yunnan, Hunan, Sichuan, Jilin, Fujian, Hubei, Shanxi, Heilongjiang, Guizhou
30–60 Mtce	Liaoning, Shanghai, Zhejiang, Anhui, Hebei, Shanxi
>60 Mtce	Henan, Guangdong, Inner Mongolia, Jiangsu, Shandong

Figure 5. The distribution of 30 provinces based on the energy consumption for thermal electricity generation.

4.3. The Results of IDA

The IDA method is applied to identify the contributions of different factors to the overall changes in CO₂ emissions arising from China's thermal electricity generation at provincial level. The results of IDA in absolute terms are shown in Figure 6.

Figure 6. Decomposition of changes in CO₂ emissions across the 30 provincial power grids in China, 2000–2013 (absolute terms).

In Jiangsu, Shandong, and Inner Mongolia provincial power grids, the absolute change in CO₂ emissions exceed 200 Mt. The IDA results indicate that the decomposition profiles of Jiangsu and Shandong were similar during the study period, as both economic activity and energy intensity compelled an increase in CO₂ emissions, whereas the carbon factor had the opposite influence. As for Inner Mongolia, the influence of the carbon factor was different for it contributed to an increase in CO₂ emissions, although the value was very small.

The second group of provincial power grids comprises Shanxi, Henan, Guangdong, Zhejiang, Hebei, and Xinjiang, whose CO₂ emissions increased by 111–183 Mt during 2000–2013. Noteworthy, economic activity played a decisive role in the increase in CO₂ emission in the Henan power grid, whereas energy intensity and carbon factor had almost no influence on CO₂ emissions if compared to the economic activity's effect. As for Shanxi and Xinjiang, both economic activity and energy intensity effects were responsible for the increase of CO₂ emissions. The effect of energy intensity was rather strong in Xinjiang, implying a need for further energy efficiency in this provincial power grid. In Guangdong and Hebei provincial power grids, CO₂ emissions increased due to the economic growth (i.e., economic activity), yet energy intensity pushed the CO₂ emissions down, leading to a decrease of 53 Mt and 43 Mt, respectively. Zhejiang experienced a similar increase to that of Guangdong and Hebei, however, the decrease due to energy intensity was rather meager, by 6 Mt.

Guizhou, Liaoning, Fujian, Shanxi, Ningxia, and Anhui all belong to the third group with their CO₂ emissions increasing by 71–96 Mt during 2000–2013. Guizhou, Shanxi, Fujian, and Ningxia are similar in their decomposition structures, for the increase of CO₂ emissions were caused by both economic activity and intensity, whereas economic activity had the decisive effect on the increase in emissions. As regards Liaoning and Anhui, the CO₂ emissions decreased due to the energy intensity and carbon factor, although these effects were offset by the positive contribution of economic activity.

Provincial power grids with small increases in CO₂ emissions are rather different in their decomposition results. The forth group of provincial power grids comprises 13 provincial power grids (i.e., Qinghai, Hainan, Heilongjiang, Chongqing, Sichuan, Tianjin, Yunnan, Jilin, Jiangxi, Guangxi, Hubei, Gansu, and Hunan), where CO₂ emissions increased by 10–55 Mt during 2000–2013. Heilongjiang, Sichuan, Tianjin, Jilin, Yunnan, and Hubei shared the similar decomposition profiles for the increases of CO₂ emissions in these provincial power grids, which were pushed up by economic activity, while energy intensity contributed to a decrease in CO₂ emissions. However, in Qinghai, Hainan, Chongqing, Guangxi, Gansu, and Hunan, both economic activity and intensity pushed up the CO₂ emissions. Especially, for Jiangxi, the increase of CO₂ emissions was under the control of economic activity, whereas the effect of other two factors is negligible. In general, the carbon factor has a very slight influence on the CO₂ emissions in the provincial power grids within this group.

The last group of provincial power grids comprises Beijing and Shanghai, because only these two provincial power grids showed a decrease in CO₂ emissions during the study period. Meanwhile, the two provincial power grids shared the same pattern of decomposition. Obviously, the decreases of CO₂ emissions were mainly driven by energy intensity. The values of the carbon factor were negative for both provincial power grids, yet this effect was not a decisive one. This implies that energy intensity remains the most significant factor behind the decrease of energy-relevant CO₂ emissions from thermal electricity generation in the last group.

Figure 7 exhibits the relative decomposition for the 30 provincial power grids in China to measure the contribution degree of different factors to CO₂ emissions from thermal electricity generation. It is worth pointing out that the contributions of all the factors are normalized in regards of the overall CO₂ emission changes. Noticeably, for China's 30 provincial power grids, economic activity had a decisive effect on the increase in CO₂ emissions from thermal electricity generation during 2000–2013, with the exception for Beijing and Shanghai. Though the relative contribution of energy intensity varied across the 30 provincial power grids, energy intensity played an important role in the reduction of CO₂ emissions in Beijing, Heilongjiang, Liaoning, Jilin, Shanghai, Anhui, and Sichuan. The effect of the carbon factor was relatively small compared to the other factors, yet the changes of the carbon factor

usually compelled the CO₂ emissions to dwindle, with the exception of Heilongjiang, Guangdong, and Ningxia power grids. This finding implies that fuel-mix should be adjusted in the latter three provincial power grids to control the CO₂ emissions from thermal electricity generation.

Figure 7. Decomposition of changes in CO₂ emissions across the 30 provincial power grids in China, 2000–2013 (relative terms).

In order to analyze the temporal developments in driving factors of CO₂ emissions from thermal electricity generation in China, the results of IDA have been aggregated across the 30 provincial power grids (see Figure 8). It is obvious that, in the period before 2005, the energy intensity effect pushed the CO₂ emissions to increase while afterwards the energy intensity pushed the CO₂ emissions to decrease, excluding the period 2010–2011. Note that during 2000–2005 the increase in the CO₂ emissions related to the energy intensity increase continued until the period 2004–2005.

Figure 8. Decomposition of changes in CO₂ emissions for the whole group of 30 provincial power grids in China, 2000–2013.

As for the impact of economic activity, it is the main reason for the increase of CO₂ emissions in China's thermal electricity generation. The direction of the activity effect remained constant during the

study period, though its level varied with time. In 2000–2007, the increase in CO₂ emissions caused by economic activity grew progressively year by year. Afterwards, the economic-related growth in CO₂ emissions fluctuated between 259 Mt and 310 Mt per annum, and the values tended to be stable after 2010–2011. In comparison, the carbon factor impact on CO₂ emission is meager and negative during 2000–2013, with exceptions for 2000–2001, 2002–2003, and 2010–2011.

In general, CO₂ emissions from thermal electricity in China increased by 2547 Mt for the 30 studied power grids during 2000–2013. The major factor behind this change was economic activity, which rendered an increase of 3092 Mt. Energy intensity and carbon factor decreased the CO₂ emissions by 403 Mt and 91 Mt, respectively. In conclusion, the increase in economic activity is the key factor contributing to the increase of 121.4%, while changes in energy intensity and carbon factor partially offset the increase by −17.8% and −3.6%, respectively. Therefore, economic development and the subsequent increase in demand for electricity were the decisive reasons behind the increase of CO₂ emissions from thermal electricity generation in China. However, a gain in energy efficiency was an effective approach to reduce the CO₂ emissions, whereas the changes in the fuel-mix had a relatively weak influence on the reduction.

5. Environmental Efficiency and Shadow Prices

5.1. Data Sources

To model the production process, this study includes three inputs in the slack-based DEA model. These inputs are emission-related coal fuel (in Mtce), emission-related non-coal fuel (in Mtce) and installed capacity (in 10 KW) of provincial thermal electricity generation. The electricity produced by thermal power plants is treated as a desirable output, whereas the undesirable output is the CO₂ emissions arising from the thermal electricity generation. Note that the data for CO₂ emission are the same as that used in IDA analysis. The data are collected for the 30 provinces in China. According to Table 1 (see Section 4.1), the primary energy use in China's thermal electricity generation can be divided into coal fuel and non-coal fuel to reflect the different roles of the fuel types. The data about electricity produced by thermal power plants (in billion kW·h) are obtained from different issues of CESY [64]. As for the installed capacity, it is derived from the issues of China Electric Power Industry Statistics Analysis [67] and Statistical Information Department of China Electricity Council. Table 5 presents the mean values of inputs and outputs for the 30 provincial power grids during 2000–2013.

Table 5. Mean values of both inputs and outputs for 30 provincial power grids, 2000–2013.

Provinces	Inputs			Desirable Output	Undesirable Output
	Coal Fuel (Mtce)	Non-Coal Fuel (Mtce)	Installed Capability (10 ⁴ kW)	Electricity (10 ⁸ kW·h)	CO ₂ Emissions (Mt)
Beijing	5.21	0.48	441	228	15.08
Tianjin	12.67	0.22	786	397	35.32
Hebei	51.27	2.7	2750	1471	143.62
Shanxi	52.61	1.98	2981	1471	147.56
Inner Mongolia	71.58	0.66	3370	1490	199.06
Liaoning	35.86	1.11	2030	968	100.51
Jilin	19.41	0.27	929	406	53.88
Heilongjiang	24.69	0.51	1398	614	68.98
Shanghai	37.44	1.57	1512	757	105.94
Jiangsu	73.39	1.76	4506	2303	204.65
Zhejiang	42.67	2.43	3204	1403	121.77
Anhui	51.71	0.89	1895	906	143.62
Fujian	20.11	0.74	1469	641	56.62
Jiangxi	14.32	0.39	892	371	39.9
Shandong	73.98	2.49	4633	2203	207.1
Henan	59.06	1.28	3382	1550	164.46
Hubei	20.08	1.03	1339	543	56.17
Hunan	17.2	0.75	1153	473	48.03
Guangdong	54.11	9.32	4100	1953	167.9
Guangxi	11.85	1.34	789	327	33
Hainan	2.63	0.21	227	84	7.55

Table 5. Cont.

Provinces	Inputs			Desirable Output	Undesirable Output
	Coal Fuel (Mtce)	Non-Coal Fuel (Mtce)	Installed Capability (10 ⁴ kW)	Electricity (10 ⁸ kW·h)	CO ₂ Emissions (Mt)
Chongqing	8.58	0.55	523	240	24.15
Sichuan	18.54	0.38	1025	404	51.85
Guizhou	24.94	0.36	1321	675	69.18
Yunnan	16.24	0.72	796	337	45.26
Shannxi	22.9	0.43	1370	667	63.83
Gansu	14.52	0.12	865	405	40.32
Qinghai	3	0.03	152	78	8.38
Ningxia	16.37	0.22	787	388	45.7
Xinjiang	16.01	0.3	934	380	44.76

5.2. Environmental Efficiency

The efficiency scorers were estimated for the pooled data set comprising all the provinces and time periods. According to Figure 9 below, the highest mean efficiency score was observed in 2013 at 0.37, whereas the minimum value was noticed in 2000 at 0.29. However, although three slight declines were observed for time periods 2001–2002, 2003–2005, and 2007–2008, the period of 2008–2013 marked an upward trend of efficiency scores, which indicated an increasing trend in environmental performance.

Figure 9. Weighted mean environmental efficiency, 2000–2013. Note: provincial GDP is used for weighting.

The convergence in efficiency scores is another important aspect of analysis. Notably, the CV for environmental efficiency scores demonstrated a downward tendency during 2000–2013 (see Figure 10), which meant that the 30 provincial power grids in China achieved a certain degree of convergence in regard to environmental performance. Nevertheless, this process was subdued since 2010. Anyhow, the CV went down from 0.58 in 2000 to 0.41 in 2013. Moreover, the CV reached its peak in 2001 at 0.67 and attained its minimum value in 2010 at 0.28. Therefore, the 30 provincial power grids in China managed to converge in regards to environmental performance along with an increase in the mean efficiency, but this process has been subdued since 2010.

Figure 10. Variation in environmental efficiency across the 30 provincial power grids, 2000–2013. Note: CV stands for coefficient of variation.

As the slack-based DEA model considers both desirable and undesirable outputs, the higher values of efficiency scores means lower slacks of inputs and/or outputs. It is worth to emphasize that this study does not decompose the efficiency scores so as to make the research concise and easy to understand.

The mean efficiency scores during the study period for each provincial power grid are shown in Table 6. Guizhou, Beijing, Ningxia, Tianjin, and Shanxi attained the highest scores (efficiency scores of these provincial power grids ranged in between 0.46 and 0.63). By comparison, Anhui, Heilongjiang, Inner Mongolia, Jilin, Shanghai, Yunnan, and Sichuan provincial power grids were attributed with the lowest scores (efficiency scores of these provincial power grids ranged in between 0.17 and 0.24). The efficiency scores, thus, imply a substantial performance gap between the best- and worst-performing provincial power grids. In general, the efficiency scores were not very high for only two provincial power grids (e.g., Guizhou and Beijing), obtaining scores higher than 0.5, indicating that increase in energy intensity is urgently needed in China's thermal electricity sector. However, through several rounds of technical reform, the emission reduction technology of China's active coal-fired power units has reached the leading level of the world, and the energy-saving potential has been fully tapped. Indeed, with the rapid development of renewable energy in China, the utilization time of thermal power equipment that has reduced constantly in recent years may be resulting in the low environmental efficiency, especially in those provincial power grids with low efficiency scores.

Table 6. Mean environmental efficiency scores for 30 provincial power grids, 2000–2013.

Provinces	Year	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	Mean	Rank
Beijing		0.38	0.41	0.42	0.42	0.39	0.37	0.43	0.44	0.52	0.58	0.64	0.66	0.80	1.00	0.53	2
Tianjin		0.42	0.46	0.49	0.79	0.51	0.47	0.45	0.47	0.43	0.37	0.39	0.41	0.40	0.42	0.46	4
Hebei		0.38	0.40	0.40	0.39	0.40	0.38	0.35	0.38	0.35	0.34	0.29	0.30	0.33	0.34	0.36	13
Shanxi		0.96	1.00	0.52	0.56	0.37	0.39	0.34	0.34	0.28	0.27	0.33	0.35	0.35	0.33	0.46	5
Inner Mongolia		0.26	0.22	0.23	0.26	0.30	0.24	0.23	0.23	0.19	0.21	0.21	0.18	0.19	0.25	0.23	26
Liaoning		0.27	0.33	0.36	0.34	0.31	0.32	0.35	0.36	0.36	0.34	0.26	0.26	0.27	0.22	0.31	17
Jilin		0.26	0.22	0.25	0.21	0.20	0.21	0.22	0.24	0.19	0.18	0.18	0.15	0.14	0.14	0.20	27
Heilongjiang		0.19	0.23	0.23	0.25	0.27	0.29	0.24	0.29	0.25	0.20	0.22	0.21	0.23	0.30	0.24	25
Shanghai		0.07	0.08	0.08	0.10	0.09	0.08	0.07	0.07	0.06	0.08	0.41	0.52	0.49	0.40	0.19	28
Jiangsu		0.34	0.37	0.39	0.42	0.40	0.38	0.42	0.47	0.48	0.46	0.49	0.51	0.50	0.42	0.43	6
Zhejiang		0.28	0.30	0.32	0.32	0.26	0.23	0.31	0.36	0.37	0.38	0.42	0.44	0.44	0.47	0.35	14
Anhui		0.02	0.04	0.08	0.54	1.00	0.05	0.03	0.03	0.02	0.04	0.40	0.44	0.37	0.36	0.24	24
Fujian		0.31	0.24	0.38	0.49	0.48	0.44	0.41	0.45	0.42	0.43	0.38	0.42	0.37	0.37	0.40	9
Jiangxi		0.12	0.15	0.20	0.32	0.26	0.25	0.29	0.27	0.27	0.28	0.25	0.35	0.34	0.36	0.27	23
Shandong		0.52	1.00	0.38	0.28	0.36	0.33	0.32	0.33	0.36	0.36	0.34	0.34	0.33	0.36	0.40	8
Henan		0.31	0.30	0.32	0.30	0.28	0.28	0.28	0.31	0.30	0.33	0.26	0.34	0.33	0.36	0.31	18
Hubei		0.21	0.29	0.30	0.31	0.16	0.22	0.27	0.30	0.22	0.32	0.25	0.30	0.28	0.34	0.27	22
Hunan		0.24	0.23	0.23	0.26	0.28	0.42	0.29	0.29	0.27	0.33	0.26	0.28	0.25	0.29	0.28	20
Guangdong		0.31	0.31	0.32	0.39	0.33	0.31	0.31	0.34	0.31	0.35	0.36	0.40	0.37	0.39	0.34	16
Guangxi		0.23	0.22	0.26	0.41	0.50	0.16	0.19	0.20	0.21	0.28	0.33	0.29	0.26	0.33	0.28	21
Hainan		0.23	0.21	0.20	0.37	0.45	0.51	0.53	0.48	0.43	0.40	0.42	0.46	0.44	0.43	0.40	10
Chongqing		0.13	0.73	1.00	0.35	0.21	0.25	0.23	0.26	0.20	0.24	0.34	0.28	0.28	0.31	0.34	15
Sichuan		0.05	0.07	0.15	0.17	0.13	0.11	0.12	0.10	0.09	0.22	0.34	0.28	0.28	0.22	0.17	30
Guizhou		0.62	0.77	1.00	1.00	0.97	0.93	1.00	0.33	0.29	0.37	0.35	0.37	0.40	0.41	0.63	1
Yunnan		0.32	0.16	0.22	0.17	0.24	0.14	0.16	0.15	0.13	0.22	0.17	0.12	0.05	0.09	0.17	29
Shannxi		0.32	0.29	0.27	0.39	0.33	0.37	0.43	0.42	0.34	0.30	0.36	0.49	0.54	0.56	0.39	12
Gansu		0.36	0.38	0.40	0.41	0.53	0.43	0.42	0.41	0.39	0.33	0.35	0.34	0.35	0.36	0.39	11
Qinghai		0.31	0.41	0.52	1.00	0.60	0.29	0.24	0.24	0.38	0.44	0.39	0.36	0.34	0.39	0.42	7
Ningxia		0.41	0.39	0.30	0.32	0.52	0.83	0.89	0.93	0.35	0.31	0.30	0.37	0.39	0.39	0.48	3
Xinjiang		0.24	0.23	0.25	0.26	0.26	0.31	0.32	0.35	0.34	0.29	0.34	0.36	0.31	0.38	0.30	19

5.3. Shadow Prices

Shadow prices can be calculated by Equation (16) to analyze the possibilities for reduction in the CO₂ emissions arising from thermal electricity generation in China. Figure 11 presents the weighted mean shadow price for the 30 provinces, with the CO₂ emission values used as the weight factors. According to Figure 11, the mean shadow price (falling within the range of 519–667 Yuan/ton) had been following a positive trend during 2000–2013 and reached its peak of 667 Yuan/ton at 2013, which indicates that the reduction of CO₂ emissions in thermal electricity generation is becoming more and more expensive given the underlying productive technology. Based on the analysis above, reasonable targets and allocation across the provincial power grids are required to reduce the CO₂ emissions from thermal electricity generation.

Figure 11. Weighted mean CO₂ emission shadow price, 2000–2013. Note: carbon emission is used as the weighting factors.

According to Figure 12, there has been an obvious decline in variation of shadow prices across the 30 provincial power grids, yet the period of 2011–2013 marked an increasing CV. Especially, the highest CV for the shadow prices was observed in 2003 at 0.28, whereas the minimum value was noticed in 2011 at 0.08. Corresponding to the convergences of efficiency scores, the analysis shows that the 30 provincial power grids managed to secure the convergence in terms of shadow prices, yet this process has been subdued since 2010.

Figure 12. Variation in shadow prices across the 30 provincial power grids. Note: CV stands for coefficient of variation.

Table 7 presents the mean values of abatement costs at provincial level. Note that, for easier understanding, the base year of shadow prices is 2013 instead of 2000. According to Figure 12 and Table 7, shadow prices of CO₂ emissions resulting from thermal electricity generation are rather different across the 30 provincial power grids. Therefore, it might be concluded that the costs associated with environmental pressures have not been leveled in China's thermal electricity generation.

Table 7. Mean abatement costs for 30 provincial power grids, 2000–2013.

Provinces/Provincial Power Grids	Abatement Costs			
	Mean (Yuan/ton in 2013 Price)	Rank	CV	Rank
Beijing	711	3	0.142	12
Tianjin	594	20	0.155	9
Hebei	615	13	0.087	20
Shanxi	590	21	0.188	6
Inner Mongolia	560	25	0.039	27
Liaoning	612	14	0.055	24
Jilin	558	26	0.093	16
Heilongjiang	606	15	0.041	26
Shanghai	560	24	0.179	8
Jiangsu	619	12	0.052	25
Zhejiang	694	4	0.023	30
Anhui	464	29	0.386	2
Fujian	656	6	0.089	18
Jiangxi	628	11	0.079	21
Shandong	631	10	0.093	17
Henan	603	18	0.065	23
Hubei	654	7	0.104	15
Hunan	650	8	0.089	19
Guangdong	711	2	0.026	28
Guangxi	674	5	0.153	10
Hainan	722	1	0.147	11
Chongqing	646	9	0.296	4
Sichuan	597	19	0.118	14
Guizhou	466	28	0.332	3
Yunnan	569	23	0.137	13
Shaannxi	605	17	0.068	22
Gansu	578	22	0.182	7
Qinghai	512	27	0.271	5
Ningxia	444	30	0.388	1
Xinjiang	605	16	0.024	29

The top ten shadow prices are observed in Hainan, Guangdong, Beijing, Zhejiang, Guangxi, Fujian, Hubei, Hunan, Chongqing, and Shandong power grids (shadow prices for these provincial power grids fell in the range of 631–722 Yuan/ton). Meanwhile, based on the relative results of IDA (see Figure 7), the activity effect usually induces an increase of CO₂ emissions in these highest-ranking provincial power grids. In conclusion, the application of innovative energy technologies should go beyond the state-of-the-art in the ten provincial power grids, which calls for substantial investment in thermal electricity sector. Meanwhile, the IDA results show that changes in the fuel-mix would facilitate the decrease in CO₂ emission from the ten provincial power grids.

The lowest carbon shadow prices are observed in Yunnan, Shanghai, Inner Mongolia, Jilin, Qinghai, Guizhou, Anhui, and Ningxia. Especially, Ningxia, Anhui, and Guizhou show the lowest mean carbon shadow prices of 444, 464, and 466 Yuan/ton, respectively. The forth lowest shadow prices are observed for Qinghai, namely 512 Yuan/ton. The carbon shadow prices range between 558–569 Yuan/ton for Yunnan, Shanghai, Inner Mongolia and Jilin. These provincial power grids, thus, feature the highest potential for the reduction of CO₂ emissions in China's thermal electricity sector.

The IDA results might be helpful in providing guidelines for further development of the Chinese power sector to curb the CO₂ emissions from the thermal electricity sector. Based on Figures 6 and 7, one can conclude that Inner Mongolia, Heilongjiang, Guangdong, and Ningxia require improvements in the fuel-mix to reduce the carbon factor. Turning to Shandong, Shanxi, Fujian, and Ningxia, increasing energy efficiency (lowering energy intensity) might be the primary path for CO₂ emission reduction. Even though Hebei, Jiangxi, Zhejiang, and Tianjin have seen decreases in both carbon factor and energy intensity, their CO₂ emissions still remain relatively high. Therefore, prospective implementation of energy technologies is significant in both areas (i.e., carbon factor and energy intensity) for Hebei, Jiangxi, Zhejiang, and Tianjin.

6. Conclusions

In this study, energy-related CO₂ emissions arising from China's thermal electricity generation have been analyzed at the provincial level. Methodologically, the research took two major directions. First, the Shapley Index was used for IDA to discover the main reasons behind the changes in CO₂ emissions resulting from China's thermal electricity generation. Second, the Slack-based Model was applied and shadow prices were calculated to measure provincial environmental efficiency and the abatement costs of CO₂ emissions.

(1) The energy use in China's 30 provincial thermal electricity generation grids increased by 228% through the years 2000–2013, yet the energy-related CO₂ emissions increased by 216%, suggesting that though energy use has a strong influence on CO₂ emission from China's thermal electricity sector, there are still other factors influencing the CO₂ emission, such as technology and management efficiency. Meanwhile, the AAGRs of CO₂ emissions from China's thermal electricity generation varied across the 30 studied provincial power grids during 2000–2013. Especially, Ningxia (17.9%), Inner Mongolia (17.44%), and Xinjiang (14.6%) exhibited the highest AAGRs, whereas Shanghai and Beijing are the only two power grids that have negative growth rates of −3.29% and −0.46%, respectively. Shanghai and Beijing, thus, present good performance in CO₂ emission reduction among the 30 studied provinces during the period 2000–2013, especially for Shanghai.

(2) Unlike the traditional classification, the 30 provincial power grids in China can be divided into four classes (see Figure 4) based on the mean energy consumption of provincial thermal electricity generation during the study period. Accordingly, Henan, Guangdong, Inner Mongolia, Jiangsu, and Shandong consumed the highest amounts of energy (more than 60 Mtce), whereas Hainan, Qinghai, Beijing, Chongqing, Tianjin, Guangxi, Gansu, and Jiangxi consumed the lowest amounts (less than 15 Mtce). This may be because the energy consumption of different provincial thermal electricity generation is corrected with resource endowment, economic development level, and population size, but with a modest impact of geographic position. However, ensuring transmission of the renewable electricity from Qinghai and Gansu to the provinces of high energy consumption (e.g., Henan, Guangdong, Inner Mongolia, Jiangsu, and Shandong) can reduce total energy use from thermal electricity generation.

(3) Economic activity played a decisive role as a factor behind the increase in CO₂ emissions from thermal electricity generation during 2000–2013, with the exception for Beijing and Shanghai. Though the contributions of energy intensity effect varied across the 30 provinces, energy intensity played an important part in the reduction of CO₂ emissions in Beijing, Heilongjiang, Liaoning, Jilin, Shanghai, Anhui, and Sichuan. In regard to carbon factor, it usually induced a decrease in the CO₂ emissions, excluding Jilin, Guangdong, and Ningxia provincial power grids. Both energy intensity and carbon factor can promote the reduction of CO₂ emissions in China's thermal electricity generation, yet energy intensity has a stronger effect, especially for Beijing, Heilongjiang, and Shanghai.

(4) The aggregated IDA results of the 30 provincial power grids indicate that the economic activity effect pushed the CO₂ emission grew progressively before 2007, whereas the economic-related growth in CO₂ emissions changed marginally afterwards implying that economic activity had a relatively stable influence on CO₂ emission from thermal electricity generation since 2007. Though the changes

in CO₂ emissions caused by energy intensity was positive during 2000–2005, energy intensity pushed the CO₂ emissions to reduce since 2006. Compared with the other two forces, carbon factor had no obvious impact on CO₂ emission during 2000–2013.

(5) The efficiency scorers of the 30 aggregated provincial power grids displayed an upward trend during 2008–2013, meaning a positive trend in environmental performance of China's thermal electricity generation. However, the mean environmental efficiency scores (falling within the range of 0.17–0.63) of different provinces were not very high in general. Especially, Anhui, Heilongjiang, Inner Mongolia, Jilin, Shanghai, Yunnan, and Sichuan provincial power grids were observed with the lowest scores (falling within the range of 0.17–0.24), which implies that there is still a great deal of room for improvement in these provinces' thermal electricity generation. Though the emission reduction technology of China's active coal-fired power units is quite advanced, the utilization time of thermal power equipment reduced continuously in recent years due to the high-speed development of renewable energy in China, which may lead to the low environmental efficiency especially in these provincial power grids with low efficiency scores. Therefore, to tap the potential for CO₂ emission reduction in China's thermal electricity generation, the innovation of mechanisms and measures of the market may be more effective compared with compulsory technical standards.

(6) The mean shadow prices (falling within the range of 519–667 Yuan/ton) of the 30 aggregated provinces had exhibited an increasing trend during the studied period and reached its peak of 667 Yuan/ton at 2013. This upward tendency may suggest that the reduction of CO₂ emissions from China's thermal electricity generation is becoming more and more expensive given the underlying productive technology. However, the findings show that there are some provincial power grids with relatively low carbon performance and the lowest carbon shadow prices were obtained in Yunnan, Shanghai, Inner Mongolia, Jilin, Qinghai, Guizhou, Anhui, and Ningxia. These provincial power grids, therefore, feature the highest potential for the reduction of CO₂ emissions in China's thermal electricity generation.

(7) The convergence in efficiency scores (or shadow prices) is another important aspect to analyze the performance of CO₂ emission in China's thermal electricity generation. The 30 provincial power grids achieved a certain degree of convergence in terms of both efficiency scores and shadow prices, but this process was subdued since 2010 indicating that there is a widening performance gap among the 30 provincial power grids during 2010 and 2013. Accordingly, it is vital for the Chinese government to establish a persistent mechanism that the provincial power grids with high environmental efficiency should assist those with low ones.

(8) Given the differences existing among the 30 provincial power grids, the paper offers the following measures for the Chinese government: (i) Policies aimed at reducing energy intensity are the most effective when seeking for reduction of CO₂ emissions from thermal electricity generation and should be considered first in Inner Mongolia, Fujian, Guangxi, Hainan, Ningxia, and Xinjiang. For the increase in the CO₂ emissions caused by energy intensity is relatively high in these provinces; (ii) Promotion of renewable energy production and changes in fuel-mix should be considered in Jilin, Guangdong, and Ningxia to meet the goals of CO₂ emission reduction. Indeed, it is only in these three power grids that the carbon factor rendered an increase in the CO₂ emissions; (iii) Though the effect of both carbon factor and energy intensity can promote the reduction of CO₂ emissions from Hebei, Jiangxi, Zhejiang, and Tianjin, the CO₂ emissions are still relatively high in these provinces. Therefore, these three provinces are supposed to enhance their energy technologies in both areas (i.e., carbon factor and energy intensity); (iv) To encourage the control of CO₂ emissions in China's thermal electricity sector, China should accelerate the improvement of the present carbon trading market (which includes the thermal electricity generation) in trading framework, basic technology and talent reservation. The reforms regarding the electricity dispatch should be furthered in ensuring priority for more efficient grid systems and power plants. In this way, the removal of the backward capacities would be encouraged.

Further research is necessary in regards to carbon emission efficiency and productivity in China's thermal electricity generation. More factors (e.g., energy structure, population, and electricity output) can be included in the IDA model to present a more comprehensive view towards CO₂ emissions from thermal electricity generation at the province-level. Additionally, a comparison of different environmental efficiency measures and, e.g., the framework of by-production, can be discussed to enable deeper insights into the environmental performance of China's thermal electricity generation. Decomposing the changes in shadow prices can also enrich the analysis in the latter sense.

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