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Decomposition Analysis in Electricity Sector Output from Carbon Emissions in China

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Abstract: Carbon emissions from China's electricity sector account for about one-seventh of the global carbon dioxide emissions, or half of China's carbon dioxide emissions. A better understanding of the relationship between CO_2 emissions and electric output would help develop and adjust carbon emission mitigation strategies for China's electricity sector. Thus, we applied the electricity elasticity of carbon emissions to a decoupling index that we combined with advanced multilevel Logarithmic Mean Divisia Index tools in order to test the carbon emission response to the electric output and the main drivers. Then, we proposed a comparative decoupling stability analysis method. The results show that the electric output effect played the most significant role in increasing CO_2 emissions from China's electric sector. Also, "relative decoupling" was the main state during the study period (1991–2012). Moreover, the electricity elasticity of CO_2 emissions had a better performance regarding stability in the analysis of China's electricity output.

Keywords: CO_2 emissions; electricity sector; decoupling; comparative stability analysis; China

1. Introduction

China, the biggest carbon emitter in the world, after realizing the importance and urgency of reducing carbon emissions [1,2], has taken relevant measures to cut emissions down [3,4]. The carbon dioxide (CO_2) emissions from electricity accounted for over half of total CO_2 emissions from fuel combustion in China, and about one-seventh of total CO_2 emissions from fuel combustion in the world [5]. According to some future carbon emission scenarios, the electricity sector can be regarded as the biggest carbon emitter from the sector-level perspective [6]. Thus, a deeper understanding of the decoupling of carbon emission growth from electric output and the main drivers of the decoupling process in China is a matter of cardinal significance.

In previous decomposition literatures, structure decomposition analysis (SDA) and index decomposition analysis (IDA) were the most popular tools to figure out the effects when decomposing [7–12]. The IDA method has been widely used in previous studies, successfully quantifying the impact of different issues so far [13]. Tracking new developments, Ang discussed the method formulation using an index number framework [14], made a detailed review of various methods, and compared the advantages and disadvantages of various decomposition tools. He concluded that the Logarithmic Mean Divisia Index (LMDI) method was the preferred method, because of its perfect theoretical framework, adaptability, ease of use, and result interpretation, as well as other desirable properties in the context of decomposition analysis [15]. This is a complete decomposition method without residuals, which was generalized by Sun to analyze energy consumption in China [13]. Ang and Liu later modified the original model to handle negative values in the LMDI technique [16]. Many studies then applied this technique due to this advantage; for example, Cansino et al. analyzed the influencing factors of different sectors by using a multisector analysis approach [17]. Paul and Bhattacharya [18], Shahbaz, M. [19], Wang et al. [11,12], and Lise [20] also conducted comprehensive analyses of the carbon emission drivers in India, Portugal, China, and Turkey based on their regional characteristics, respectively. Xu et al. decomposed the changes of China's energy-related air pollutant (NOx, $PM_{2.5}$, and SO_2) emissions into various factors by structural decomposition analysis (SDA) [21]. Hu et al. calculated the carbon emissions from each fuel and tested the contributions of each factor to carbon emissions in Chongqing after taking the sector differences into consideration [22]. Wang et al. uncovered the drivers of decoupling between economic growth and carbon emissions in Chinese industry [23]. Sumabat et al. carried out a decomposition analysis of CO_2 emissions from electricity generation in the Philippines [24]. Wang et al. investigated the decoupling states between economic growth and water use in Beijing, Shanghai, and Tianjin, China [25], and identified the socioeconomic drivers of decoupling economic growth from energy consumption in China and India [26]. In general, most previous CO_2 emission decomposition analysis focused on the social and economic factors, and primarily decomposed the emission changes into four main aspects: population, energy mix, energy intensity, and economic development. However, few studies have taken the sector characteristics into account when carrying out the carbon emission decomposition analysis, even though considering these properties can help policymakers develop more applicable strategies for the electricity sector. To fill this gap, we conducted our research from the perspective of electricity sector characteristics via the modified LMDI model on the basis of the extended Kaya identify [27], aiming to test the impacts of factors on carbon emissions, such as electric output, energy consumption, and conversion efficiency (instead of social and economic development), along with their contributions to decoupling.

For the decoupling research, Tapio proposed a decoupling analysis theoretical framework for the European Union (EU) to measure the relationship between CO_2 emissions and transport output or economic growth [28]. Diakoulaki and Mandaraka assessed the decoupling process of CO_2 emissions from the industrial development of the manufacturing sector in the EU [29]. Lin and Liu investigated the CO_2 emissions of the heavy industry via decomposing the decoupling index model [30]. Hu et al. applied the Tapio decoupling model to identify the drivers of carbon emissions from China's product sector [22]. Zhang et al. analyzed the decoupling state and determined the main factors that influenced the decoupling relationship by combining a decoupling model with the decomposition method [31]. However, previous studies were conducted primarily through the decoupling elasticity system or the decoupling index analysis method, and few studies compared the applicability and stability for a given region. We tried to perform a comparative stability test on the decoupling indices of the electricity sector to fill the gap. Also, the majority of the relevant literature concentrated on uncovering the decoupling relationship between carbon emissions and GDP (gross domestic product) or the added economic value of a sector. Nevertheless, few of them have focused on discussing the relationship of carbon emissions and sectoral output from the perspective of sector development rather than economic gains.

Since power generation is one of the major sources of CO_2 emissions from fossil fuel combustion [32], the electricity sector is attracting more attention, which is also becoming an increasingly important topic for researchers. Shrestha and Timilsina analyzed the roles of generation mix and fuel intensity in the thermal power carbon intensity of 12 Asian countries [33]. Wang et al. identified the socioeconomic drivers of the electricity footprint of China's industrial sectors from both the consumption side and supply side [34]. Malla discussed the contributions to electricity CO_2 emissions from three factors: electricity production, electricity generation structure, and the energy intensity of electricity generation to carbon emissions [32]. Besides, although existing studies have identified the relationship between electricity consumption and economic growth in China [35,36], most of the previous research discussed the social and economic development factors that led to changes in electricity production and consumption. They aimed to investigate the relationship between the pollution of the power sector and the socioeconomic system. Most of them discussed the main drivers of electricity CO_2 emissions without considering the characteristics of the electricity power sector. However, the policy implications aimed at this are more targeted and applicable than those of economic and social development when formulating corresponding carbon emission reduction policies in China. So, this paper chose the typical high carbon emission sector—the electricity sector—to measure the impact of electricity generation on carbon emissions.

The rest of the paper is organized as follows. Section 1 contains the literature review. Section 2 demonstrates the methods and data source. Section 3 reveals the results. Section 4 provides the conclusions and policy implications.

2. Materials and Methods

To better display the content and structure of the paper, we drew a proxy diagram to clarify the models applied in this paper (Figure 1). First, the carbon emissions from fossil fuel combustion in China's electricity power sector are calculated. Furthermore, the decoupling elasticity model is applied to identify the decoupling states through preliminary calculations of carbon emissions and output from the power sector, and compare the possibilities of reducing or slowing the CO_2 emissions of the electricity sector output. Then, the key drivers of electricity carbon emission changes from the view of the characteristics and development of the electricity sector are investigated by applying the multilevel index decomposition method (additive LMDI and multiplicative LMDI models). The decoupling index model is used to analyze the degree of decoupling (the response and synchronization degree of carbon emissions generated by the power sector to the development and output of the sector), and is then combined with the decomposition model to identify the contributions of various influencing effects. Finally, based on two different decoupling models, the electricity sector in China is used as a pilot issue in order to conduct a comparative stability test of the two widely used decoupling models.

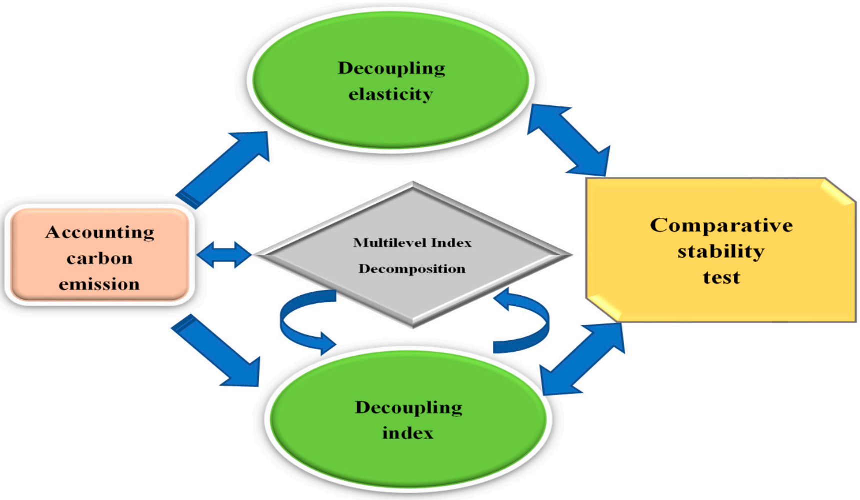

Figure 1. Flowchart of modeling concepts and methodologies.

2.1. Energy-Related CO_2 Emissions Calculation

The Intergovernmental Panel on Climate Change (IPCC) guidelines [37] put forward a method for calculating CO_2 emissions from fuels combustion, which is applied to calculate the corresponding CO_2 emissions from electricity production in China in this paper:

$$C^t = \sum_i C_i = \sum_i E_i * CF_i = \sum_i E_i * CV_i * O_i * m \quad (1)$$

C^t and C_i are the total carbon dioxide emissions from the electric power sector and the carbon emission from fuel i; and E_i (million tonnes carbon equivalent, Mtce) is the amount of energy consumed for electricity production from fuel i. CF_i (Kcal/Kg or Kcal/m^3) denotes the carbon emission coefficient of fuel i; CV_i (tC/TJ) and O_i represent the carbon content of the calorific value and the oxidation rate of given fuel, respectively, and m is the conversion fraction. The category and emission factor information of each fuel is listed in Table 1.

Table 1. Fuel category and emission factor.

Energy Category	Emission Factor ($kgCO_2$/kg or $kgCO_2$/m^3)
Raw coal	1.8801
Washed coal	2.2791
Other washed	0.7235
Briquette	1.9497
Coal gangue	0.7358
Coke	2.8604
Coke oven gas	0.8048
Blast furnace gas	0.9671
Converter gas	1.3526
Other gas	0.8956
Crude oil	3.0202
Other coking products	3.8326
Gasoline	2.9251
Diesel oil	3.0959
Fuel oil	3.1705
Liquefied petroleum gas	3.1013
Petroleum coke	3.1569
Refinery gas	3.0082
Other petroleum products	2.5274
Natural gas	2.1622

Data source: United States Agency for International Development [38].

2.2. Decoupling Elasticity Index

Using the decoupling elasticity, we established a decoupling model between CO_2 emissions and the output of the electric sector, which is exhibited in Equation (2):

$$DE = \%\Delta C/\%\Delta EO = (\frac{\Delta C}{C^0})/(\frac{\Delta EO}{EO^0}) = \frac{C^t/C^0 - 1}{EO^t/EO^0 - 1} \tag{2}$$

where DE denotes the electric output elasticity of carbon emissions; $\%\Delta C$ and $\%\Delta EO$ represent the growth rate of carbon emissions and electric output; ΔC and ΔEO are the changes of CO_2 emissions and electricity generation from the base year to the year t; and C^t, C^0, EO^t, and EO^0 stand for the CO_2 emissions and the output of the electricity sector for the year t and the base year in China, respectively. After considering a 20% variation to avoid regarding a slight change as a significant one, Tapio defined three major decoupling states and eight sub-states. Decoupling can be further divided to three sub-categories: weak decoupling, when carbon emissions and electricity output both increase (0 < decoupling elasticity < 0.8); strong decoupling, when CO_2 emissions grows and electricity output decreases (decoupling elasticity < 0); and recessive decoupling, when carbon emissions and electricity output both decrease (decoupling elasticity > 1.2). Negative decoupling contains three sub-categories: in expansive negative decoupling, CO_2 emissions and electricity output both increase (decoupling elasticity > 1.2); in weak negative decoupling, both variables decrease (0 < elasticity < 0.8); and in strong negative decoupling, CO_2 emissions decrease and electricity volume increases (elasticity < 0). Similarly, coupling is defined as a state that does not over-interpret the slight changes between decoupling and negative decoupling as significant changes, consisting of three sub-states (weak negative decoupling, expansive coupling, and recessive coupling) [28]. On this basis, the decoupling classification of carbon emissions and electricity output is shown in Table 2:

Table 2. Classification standards of CO_2 emission decoupling electric output.

Degree of Decoupling	State	ΔT	ΔC	β
Decoupling	Weak decoupling	>0	>0	$\beta < 0.8$
	Strong decoupling	>0	<0	$\beta < 0$
	Recessive decoupling	<0	<0	$\beta > 1.2$
Negative decoupling	Expansive negative decoupling	>0	>0	$\beta > 1.2$
	Strong negative decoupling	<0	>0	$\beta < 0$
	Weak negative decoupling	<0	<0	$0 < \beta < 0.8$
Coupling	Expansive coupling	>0	>0	$0.8 < \beta < 1.2$
	Recessive coupling	<0	<0	$0 < \beta < 0.8$

2.3. Decoupling Index from Multilevel Index Decomposition

Decoupling index analysis is also an important technique, which was originally advanced by Vehmas [39] and Diakoulaki [29]. We aimed to measure the synchronization of the changing trend between environmental deterioration and economic development in China's electricity sector by calculating the decoupling index.

Firstly, the carbon emission changes from each influencing factor need to be quantified. In general, the CO_2 emission changes from electricity generation can be evaluated by the Logarithmic Mean Divisia Index (LMDI) technique [11,40,41]. Especially, studies have revealed that the LMDI approach showed a relatively satisfying performance when decomposing CO_2 emissions and energy consumption [15,42–44]. In this paper, both additive LMDI and multiplicative LMDI methods from an extended Kaya identity [45–49] were adopted to give a more accurate revelation of the carbon emission changes brought from each effect. Unlike most research on decomposing electricity carbon dioxide emissions, we analyzed the electricity carbon emission from the perspective of the socioeconomic system, discussed the factors such as population and gross domestic product (GDP) per capita, and more importantly, considered the electricity sector characteristics. To be more specific, we modified the original LMDI model to improve the pertinence and applicability when discussing the electricity CO_2 emissions by focusing more on the power sector itself instead of the original factors such as population, GDP per capita, and energy intensity (energy consumption of per GDP added). Furthermore, we conducted the decomposition analysis by discussing factors such as the carbon emission factors, energy mix, gross coal consumption rate, electricity structure, and electricity production. Furthermore, a proxy diagram was drawn to give an easier understanding of the LMDI tools in Figure 2.

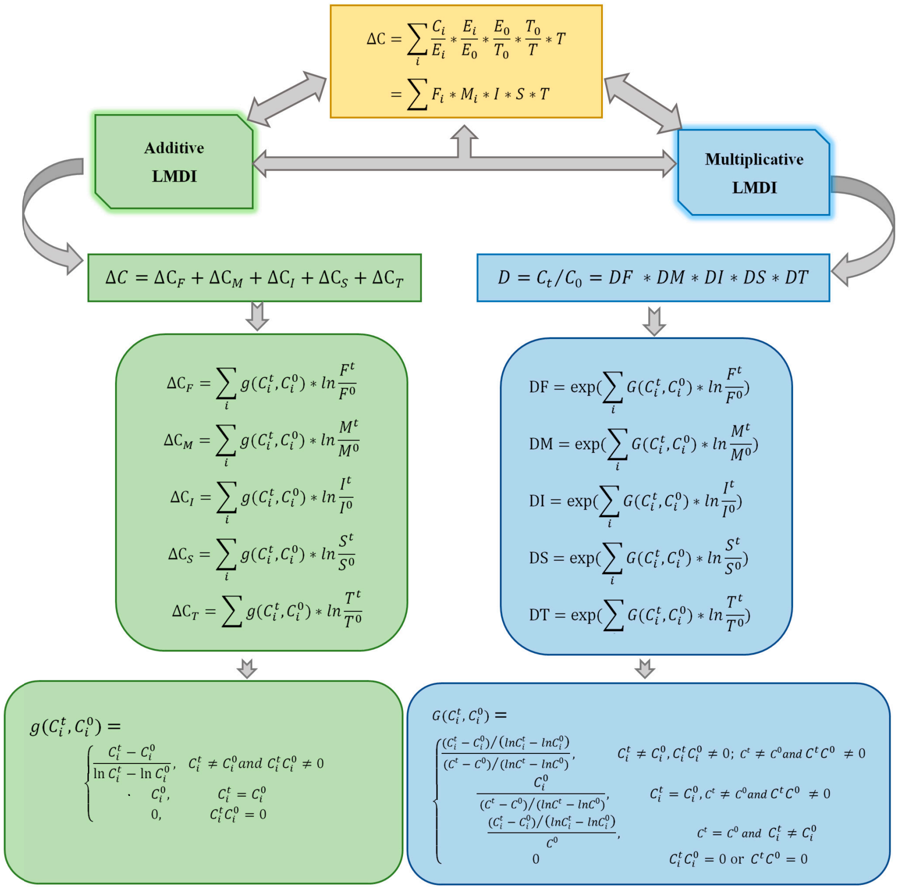

Figure 2. Diagram of additive and multiplicative Logarithmic Mean Divisia Index (LMDI) models.

Where E_0 represents the total energy consumption amount from thermal power production; and T and T_0 denote the total electricity production and fire power production, respectively. Consequently, the five effects are: carbon emission factor effect, F_i); energy mix effect, M_i; conversion efficiency effect (measured by gross coal consumption rate), I; electricity structure effect, S; and electricity output effect (measured by electricity production), T. ΔC_T, ΔC_S, ΔC_I, ΔC_M, and ΔC_F are the carbon emission changes from the five stated effects; D is the ratio of the electricity CO_2 emissions in the year t and the base year; DT, DS, DI, DM and DF are the multiplicative decomposition indices from each effect; $g\left(C_i^t, C_i^0\right)$ denotes the estimated weights for the additive LMDI; and $G\left(C_i^t, C_i^0\right)$ represents the estimated weights for multiplicative LMDI.

Due to rapid growth in China between 1995–2012, the CO_2 emissions from electricity generation increased. In this case, the decoupling relationship and its influencing factors need to be identified. The novel decoupling index model combined with the decomposition technique can offer the possibility of measuring the contributions from technology improvement, the energy consumption mix adjustment, or the new electricity generation mode to carbon mitigation. We use Δf_t and σ_t to represent the inhibiting effect on CO_2 emissions and the decoupling status of the electric power sector in China during the study period. The calculation method is shown as follows:

$$\Delta f_t = \Delta C - \Delta C_T = \Delta C_F + \Delta C_M + \Delta C_I + \Delta C_S \tag{3}$$

$$\delta_t = -\frac{\Delta f_t}{\Delta C_T} = -\frac{\Delta C_F}{\Delta C_T} - \frac{\Delta C_M}{\Delta C_T} - \frac{\Delta C_I}{\Delta C_T} - \frac{\Delta C_S}{\Delta C_T} = \delta_F + \delta_M + \delta_I + \delta_S \tag{4}$$

where δ_F, δ_M, δ_I, and δ_S denote the contributions of the carbon emission factor effect, energy mix effect, conversion efficiency effect, electricity structure effect, and electricity output effect to the decoupling process, respectively.

It should note that if $\delta_t \geq 1$, then a strong decoupling is defined, which means that the mitigation efforts grow faster than the growth of carbon emissions in the electricity generation process. Moreover, when $0 \leq \delta_t < 1$, a relative decoupling state is defined.

In other words, adjustments to measures played a positive role in cutting the carbon emissions down, such as increasing the energy conversion efficiency, improving the technology, replacing traditional high-carbon fuels with new renewable fuels, and optimizing the electricity generation structure. However, the mitigation efforts might not increase as fast as the carbon emission gains from electricity production. In addition, $\delta_t < 0$ reveals a situation in which the electricity sector produced more and more carbon emissions, but the relevant policies adjustment or technology improvement may not have come along. What's worse, other effects also contributed to CO_2 emission gains when electricity generation increased the emissions. In this situation, the development of China's electricity sector was mostly considered within the high-carbon combustion mode. The synchronization degree of the electricity generation and relevant environmental results can be measured.

2.4. Comparative Test of the Decoupling Elasticity and Index Stability

2.4.1. Graphic Stability Comparison of Decoupling Elasticity and Decoupling Index

The box plot was applied to compare the degree of stability from two different decoupling models. By analyzing the distribution interval, corresponding curve trajectory, and deviation points, the distribution information of the two decoupling indices in different years can be distinguished.

2.4.2. Decoupling Stability Coefficient

After the graphic scheme, a novel statistical tool was adopted to clarify the stability of each model. The calculation method was expressed in Equation (5):

$$SD_j = \frac{1}{N-1} \sum_{m=1}^{N} \left| \frac{x_{m+1} - x_m}{x_m} \right| \tag{5}$$

In Equation (5), SD_j denotes the stability coefficient of the decoupling tool j ($j = DE$ or δ_t); it is a coefficient to uncover the stability degree of a given decoupling tool. N is the population of samples; in this paper, it represents the amount of the studied years, and x_m and x_{m+1} are the value of the decoupling indices in the year m and the year after. The smaller the SD_j is, the more stable the tested index will be.

2.4.3. *T*-Test of Decoupling Elasticity and Decoupling Index

A Student's *t*-test was employed to further test the stability differences of the decoupling elasticity and the decoupling index. Before performing the Student's *t*-test, the prerequisites need to be checked. Firstly, the *t*-test was applied on the premise of approximately normal distribution. As a result, the normality test is first conducted by checking the normal PP plot, which is a tool to measure the relationship between the expected value and the calculated value. The test is designed to examine whether they were approximately distributed in the same line, in other words, whether a linear relationship exists between them.

The *t*-test technique is shown in the following equation:

$$\mathrm{t} = \frac{\overline{\mathrm{X}} - \mu_i}{\frac{S}{\sqrt{n}}} \tag{6}$$

where t represents the t-statistic, $\overline{\mathrm{X}}$ is the mean of the tested variables, μ_i denotes the specific value mean of the tested decoupling elasticity or decoupling index, and S and n mean the variance and the population of the tested value, respectively. We first made the hypothesis H0: $\mu_{DE} = 0$, and the electricity generation elasticity of carbon emissions was zero. The alternative hypothesis was Ha: $\mu_{DE} > 0$. All of the hypothesis and tests were conducted with the confidence level of 95%. The results can be obtained by checking the standard normal distribution table or analyzing the *p* value. When $P(t > t_{\alpha/2}) = \frac{\alpha}{2}$ or the *p* value is less than 0.05, the null hypothesis is rejected. Meanwhile, the alternative hypothesis can be accepted. If not, the null hypothesis cannot be rejected in this situation. In the decoupling elasticity test, the calculated elasticity also compared the values 0.8 and 1.2. Regarding the decoupling index test, we wanted to test the average performance of the delinking relationship measured by decoupling index, so the null hypothesis H0: $\mu_\delta = 1$. Also, the alternative $\mu_\delta < 1$ is also given. Regarding China's electricity decoupling index, a *t*-test is also conducted. What's more, in order to figure out the specific state further, we tested whether the average electricity sector had gotten rid of the linking relationship with the highly reliant development pattern by checking whether the mean value was greater than zero. As a result, we made the null hypothesis that $\mu_\delta = 0$. Accordingly, the alternative hypothesis was proposed as $\mu_\delta > 0$. After comparing the corresponding value in the normal distribution table or the *p* value, the results could be attained.

2.5. Data Source and Processing

The data used in our study period (1991–2012) were mainly obtained from the General Principles for the Calculation of Comprehensive Energy Consumption [50] and China Energy Statistical Yearbook [51]. To be more specific, the total electricity production, thermal power generation, and other energy data such as the consumption amount can be found in the China Energy Statistical Yearbook [51]. In addition, various fuels are identified to calculate the corresponding carbon emissions. To add more practical meaning to the analysis and develop more feasible measures, after the separate carbon emission calculation, the fuels were merged into three main kinds: coal, oil, and gas. The detailed categories of fuels are listed in Table 1.

3. Results and Discussion

3.1. The CO_2 Emissions from the Electricity Sector

The electricity carbon intensity is defined as the ratio of energy-related carbon emissions from electricity generation to electric output [52–54]. The changing trend in China between 1991–2012 is shown in Figure 3. As is demonstrated in the figure, the study period can be discussed from three separate spans: 1991–1997, 1998–2007, and 2008–2012. Carbon emissions increased in the first span; meanwhile, carbon emission intensity showed a downward trend.

The carbon dioxide emissions grew faster in the second phase while carbon emission intensity showed a decreasing trend in phase 2, with an average annual growth rate of −1.64%. In this period, CO_2 emissions from electricity generation grew with an average annual growth rate of 6.68%; the aggregate carbon intensity also dropped, with an average annual growth rate of 2.59%. However, the overall annual rate of carbon dioxide emissions is 8.25%, and the carbon emission intensity increased at an annual rate of 1.56%.

The slowdown of CO_2 emissions represents adjustments such as fuel-switching options and the improvement of the fire-powered technology, but after analyzing the whole period, the amount of the carbon dioxide emissions of the fire-powered electricity plants was still huge.

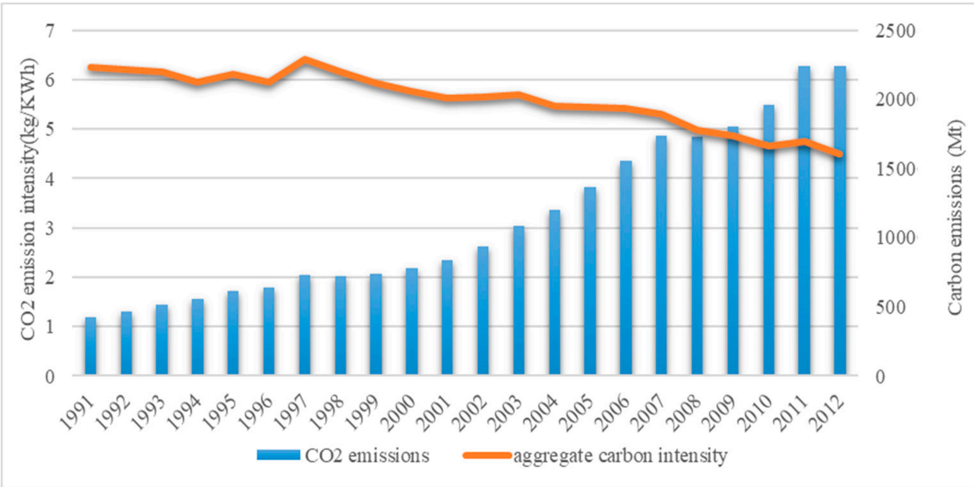

Figure 3. CO_2 emissions and carbon emission intensity from the electricity sector.

3.2. Decoupling Elasticity Analysis

As shown in Figure 4, the decoupling status varied within the specific timespan; however, the expansive coupling state and the weak decoupling state occurred with higher frequency. In fact, the decoupling state appeared only during 1993–1994, 1995–1996, 1997–2001, 2003–2004, 2007–2010, and 2011–2012. Moreover, the expected strong decoupling state only appeared in 1997–1998, 2007–2008, and 2011–2012. During these years, the link between electric output and corresponding carbon emissions showed a possibility of being broken. Also, since the decoupling elasticity can indicate how the environment responds to the electric output, after the calculation, we found that the decoupling elasticity in most years was around one, indicating that the environment response had a relatively synchronous response to China's electricity generation in most of the observed years.

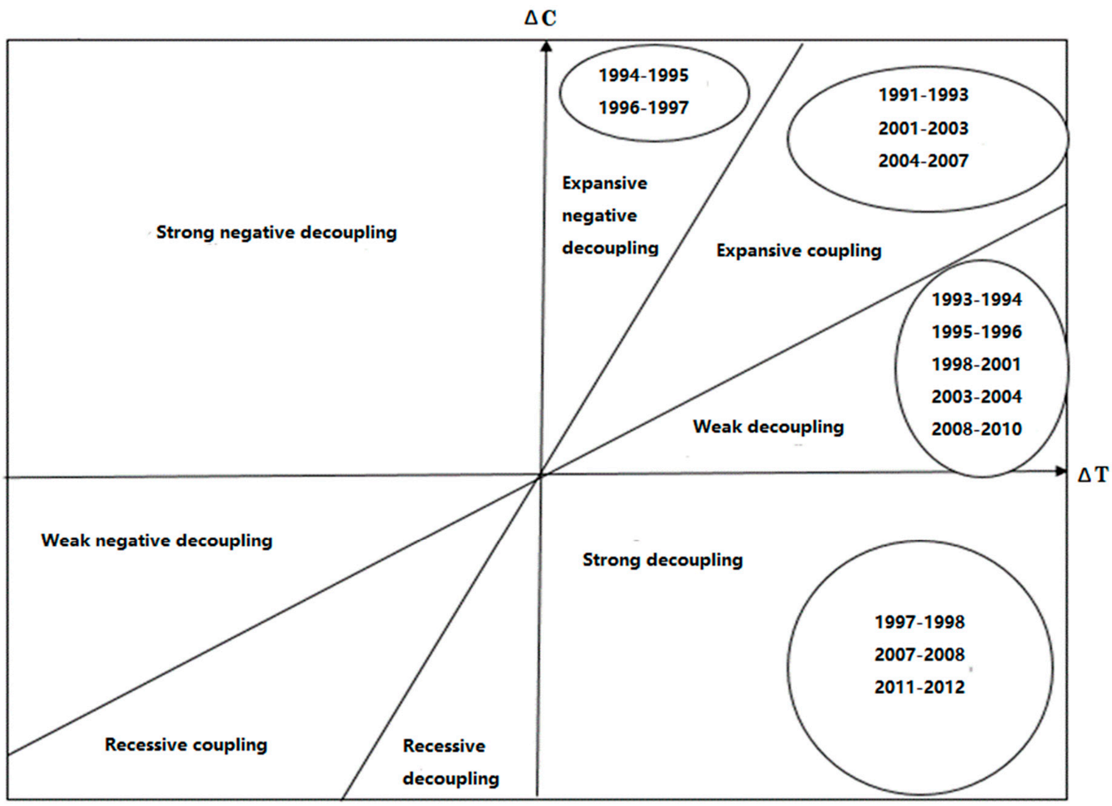

Figure 4. Results regarding the electric output elasticity of CO_2 emission results.

3.3. Drivers of Carbon Emission Identification

The contributions of the five determinants were shown in a bar graph, and corresponding electricity CO_2 emissions were shown as the green line in Figure 5. The CO_2 emissions increased during 1991–2012 in most years, except for 1998, 2008, and 2012. Besides, between 1991–1997, the changes of the carbon dioxide emissions increased faster than during the other phases at an annual rate of 10.34%. As shown in Table 3, in general, the electric power output effect contributed most to the increasing electricity carbon dioxide emissions; however, the influence of the other factors varied from year to year. The electricity intensity effect helped to curb the corresponding CO_2 emissions; the CO_2 emission mitigation mainly came from the technology development in electricity generation, which is consistent with the research before [55,56]. In addition, energy mix can pose a positive effect on the carbon emission decrease except during the years 1993, 1995, 1997, 2003, and 2004. A switch to fuels with a better generating efficiency also contributed to an efficiency improvement [55]. Even though the emission factor effect had a relative minor impact, it is closely related to decarbonization of the energy system, and should not be ignored.

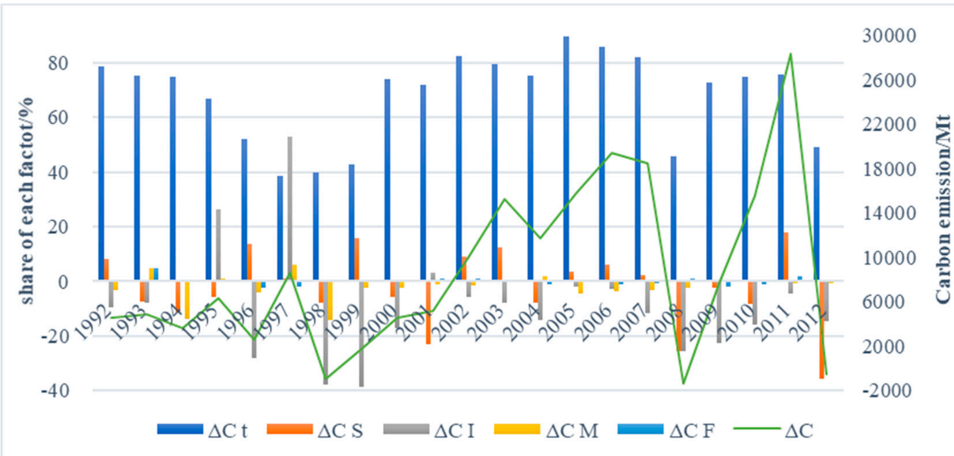

Figure 5. Decomposition of changes of electricity CO_2 emissions in China.

Table 3. Multiplicative LMDI of electricity carbon emissions.

Year	DT	DS	DI	DM	DF
1991–1992	1.1127	1.0109	0.9872	0.9956	1.0010
1992–1993	1.1118	0.9897	0.9890	1.0068	1.0068
1993–1994	1.1070	0.9852	1.0000	0.9816	0.9998
1994–1995	1.0858	0.9931	1.0327	1.0011	0.9996
1995–1996	1.0717	1.0182	0.9631	0.9947	0.9969
1996–1997	1.0514	1.0013	1.0710	1.0077	0.9977
1997–1998	1.0270	0.9948	0.9751	0.9907	0.9999
1998–1999	1.0627	1.0223	0.9466	0.9969	0.9993
1999–2000	1.0938	0.9931	0.9794	0.9970	1.0009
2000–2001	1.0924	0.9723	1.0037	0.9989	1.0014
2001–2002	1.1170	1.0123	0.9922	0.9982	1.0013
2002–2003	1.1551	1.0224	0.9856	1.0001	0.9992
2003–2004	1.1532	0.9852	0.9737	1.0034	0.9983
2004–2005	1.1347	1.0048	0.9975	0.9934	1.0007
2005–2006	1.1461	1.0098	0.9952	0.9943	0.9980
2006–2007	1.1449	1.0035	0.9806	0.9945	0.9987
2007–2008	1.0565	0.9699	0.9697	0.9973	1.0014
2008–2009	1.0714	0.9978	0.9788	0.9997	0.9983
2009–2010	1.1326	0.9863	0.9739	0.9999	0.9984
2010–2011	1.1202	1.0271	0.9933	0.9992	1.0025
2011–2012	1.0582	0.9595	0.9835	0.9993	0.9996

3.4. Decoupling Index Analysis

The decoupling index analysis was carried out after measuring the carbon emissions from each effect. The degree of synchronization and the contributions of each effect to the decoupling process can further be uncovered. The decoupling status and the contributions of every influencing factor are shown in Table 4.

Table 4. The decoupling index state and factor contribution.

Time	δ_s	δ_I	δ_M	δ_F	δ_t	Decoupling State
1991–1992	−0.1018	0.1207	0.0409	−0.0098	0.0499	relative decoupling
1992–1993	0.0974	0.1039	−0.0636	−0.0637	0.0740	relative decoupling
1993–1994	0.1469	−0.0003	0.1831	0.0020	0.3317	relative decoupling
1994–1995	0.0845	−0.3904	−0.0128	0.0049	−0.3138	no decoupling
1995–1996	−0.2604	0.5433	0.0760	0.0445	0.4035	relative decoupling
1996–1997	−0.0264	−1.3679	−0.1533	0.0462	−1.5014	no decoupling
1997–1998	0.1946	0.9484	0.3513	0.0037	1.4980	strong decoupling
1998–1999	−0.3636	0.9035	0.0505	0.0108	0.6012	relative decoupling
1999–2000	0.0774	0.2326	0.0332	−0.0101	0.3332	relative decoupling
2000–2001	0.3175	−0.0419	0.0125	−0.0154	0.2727	relative decoupling
2001–2002	−0.1108	0.0709	0.0167	−0.0120	−0.0351	no decoupling
2002–2003	−0.1537	0.1007	−0.0007	0.0058	−0.0479	no decoupling
2003–2004	0.1047	0.1867	−0.0241	0.0119	0.2792	relative decoupling
2004–2005	−0.0382	0.0199	0.0521	−0.0057	0.0281	relative decoupling
2005–2006	−0.0715	0.0349	0.0421	0.0150	0.0206	relative decoupling
2006–2007	−0.0258	0.1446	0.0409	0.0099	0.1696	relative decoupling
2007–2008	0.5566	0.5608	0.0488	−0.0258	1.1403	strong decoupling
2008–2009	0.0325	0.3111	0.0043	0.0248	0.3727	relative decoupling
2009–2010	0.1109	0.2127	0.0006	0.0125	0.3367	relative decoupling
2010–2011	−0.2355	0.0590	0.0074	−0.0220	−0.1910	no decoupling
2011–2012	0.7297	0.2947	0.0121	0.0074	1.0440	strong decoupling

As indicated in the results of the decoupling index analysis, three decoupling states were identified: strong decoupling, no decoupling, and relative decoupling. Strong decoupling offered a possible situation in which the electricity sector developed while the relevant carbon emissions dropped. The strong decoupling state was mainly brought from technological improvement, the upgrading of equipment, or a massive switch to low-carbon content fuels, especially renewables. However, strong decoupling only appeared between 1997–1998, 2007–2008, and 2011–2012. Also, a negative decoupling state occurred between 1994–1995, 1996–1997, 2001–2003 and 2010–2011. The power of factors that hindered the decoupling was stronger than the positive effects of accelerating the decoupling process. Nevertheless, in the rest of the years, the relative decoupling state was detected, indicating that even though some efforts had been made to cut down the carbon emissions, they still did not grow as fast as the electricity product gains. Due to the limitations of equipment and unsettled technology issues, the electricity generation from renewable fuels was not widely used to accelerate the decoupling process.

For the decoupling process, since relative decoupling was the main state during the study period in China's electricity sector, which reveals the possibility of reducing CO_2 emissions with no downward trend of electricity output and development. Zhang et al. concluded that the electricity generation efficiency effect plays the dominant role in decreasing CO_2 emissions [55], which is closely connected with technological improvements in electricity generation, indicating that technological innovation and the improvement of facilities usage accelerated the decoupling process of CO_2 emissions and electricity output gains.

Besides, δ_I revealed the share of the electricity intensity effect of the decoupling devotion. In most research years, it exerted a positive impact on carbon emission decoupling from electric output. Also, the electricity generation structure accelerated the decoupling in most of the observed years, which is primarily brought from the carbon emissions that had been cut by electricity generation structure changes in recent years in China [32]. It should be noted that the electric output in 2012 was 4987.55 GW·h, of which 78.05% was from thermal power. Even though it had already dropped from 81.54% in 1991, the fire-powered electricity generation was still in the dominant position throughout the whole electricity generation process. The energy mix effect (δ_M) had made decoupling efforts in most of the years during the study period, while in the rest of the years, such as 1992, 1994, 1996, 2002, and 2001, it mainly acted as a block to the CO_2 emissions decoupling from electric output. Since energy mix effects have positive effects on CO_2 emissions reduction [57], especially since the energy-efficiency targets of the 11th Five-Year Plan (approved by the Fifth Plenary, Session of the 16th Communist Party of China; it is a binding energy conservation target for governments), the switch from massive coal consumption to other fuels such as natural gas also benefited from electricity generation [58], exerting a great impact on the whole decoupling process.

Although the emission factor effect (δ_F) did not appear to be as important as the other factors in accelerating decoupling for the moment, it may become more powerful, because decarbonization could be a momentous and radical sustainability goal in the future.

3.5. Comparative Stability Test Results

3.5.1. Decoupling Stability Coefficient Analysis

After the calculation via the method in Equation (10), the results showed the difference in stability between the electricity elasticity of carbon emissions and the decoupling index.

The stability coefficient of the elasticity was 0.91, while the coefficient of the decoupling index was 2.26, revealing that for the stability, the electricity elasticity of CO_2 emissions had a better performance. Since $\boldsymbol{SD_{\delta_t} > 1}$, the expected strong decoupling was still not adequate; also, the existing relationship between the development of the electricity sector and relevant carbon emissions needed to be improved in China. The elasticity and decoupling index showed consistent results. For example, after the coupling status occurred between 2001–2003, the relative decoupling state appeared, which was attributed to the efforts made by the government, such as the electricity generation structure adjustment and the energy structure improvement. To sum up, the elasticity tool has a more stable manifestation than the decoupling index, while the decoupling index can measure the decoupling status more systematically.

3.5.2. Graphical Results of the Decoupling Indictor's Stability

As shown in Figure 6, the outlier data of the decoupling index appeared in 1996–1998, 2007–2008, and 2011–2012. Three of the abnormal points turned out to be in the state of "strong decoupling", and the abnormal points left showed the status of "no decoupling", which is consistent with the conclusion that most of the research years showed a relative decoupling state. When it comes to the decoupling elasticity, the abnormal points appeared in same period with the decoupling index; similarly, three points were demonstrated in the state of "strong decoupling", and one abnormal point presented the "no decoupling" state. In addition, the median of decoupling is between zero and one, implying that the distribution is around the relative decoupling state. What's more, by analyzing the upper quartile, the lower quartile, and the interquartile range, we figured out that the decoupling index is mostly distributed in an area that is less than one, representing the "relative decoupling" state or the "no decoupling" state. Overall, the decoupling process is not enough, suggesting that effective and promising measures and plans should be put into practice.

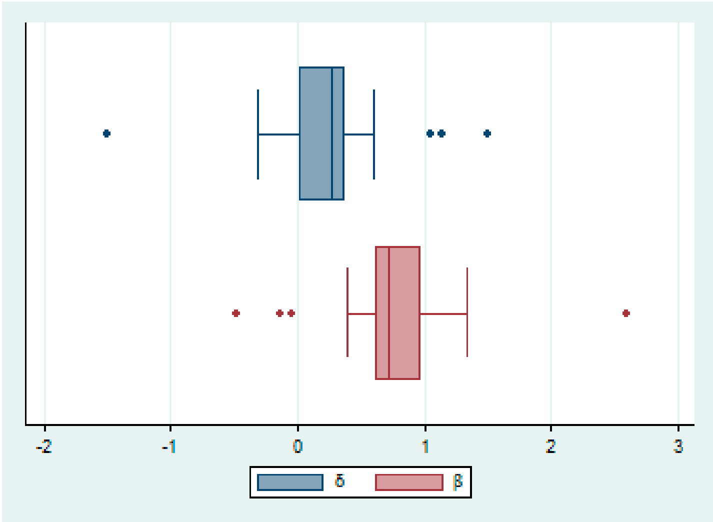

Figure 6. Box plot of the decoupling indices in China's electricity sector.

3.5.3. *T*-Test Analysis of the Decoupling Indices

By analyzing the results of the PP plot in Figures 7 and 8, the two indicators can approximately be considered as the normal distribution.

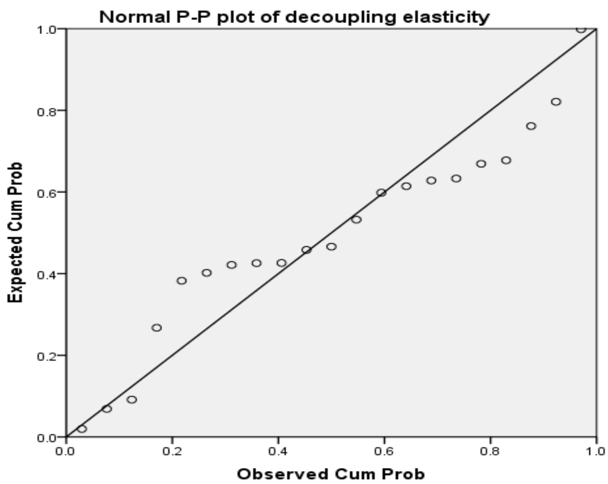

Figure 7. PP plot of China's electricity elasticity of carbon emissions.

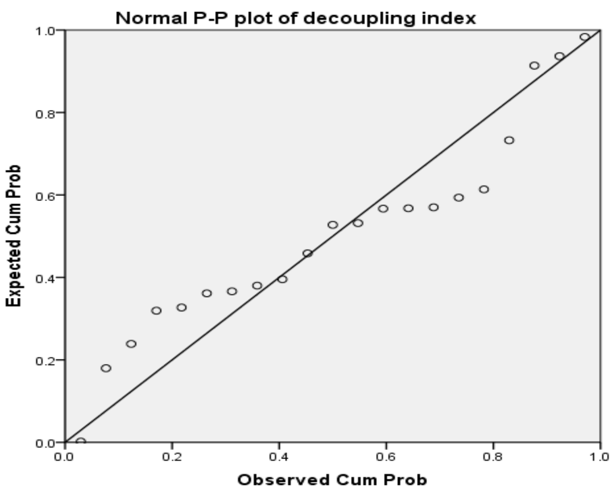

Figure 8. PP plot of China's decoupling index.

After comparing the p value with the significance level (0.05), we found that for the elasticity value, the null hypothesis was rejected, and the alternative hypothesis was adopted instead (shown in Table 5). This means that in most of the studied years, it could not get to the strong decoupling state.

Moreover, Tables 6 and 7 show the test results for testing the decoupling index with one and zero, in which the p values (0.0000 and 0.0448, respectively) were all smaller than the significance level (0.05). The alternative hypotheses were accepted at this significance level. This indicates that relative decoupling occurred more frequently, which was due to some technological improvement and the effect of the energy policies; there is still a long way to go to achieve the "perfect decoupling state". In a nutshell, more relevant policies should be developed in the future in consideration of the present situation to realize the goal of increasing the electricity production while also cutting the carbon emissions down.

Table 5. The t-test of decoupling elasticity with the test value of zero.

Variable	*t*	*p*	*Std. Err.*	*Std. Dev.*	*[95% Conf. Interval]*	
Decoupling elasticity	5.7867	0.0000	0.1331	0.6100	0.4926	1.0480

Table 6. The t-test of the decoupling index with the test value of one.

Variable	*t*	*p*	*Std. Err.*	*Std. Dev.*	*[95% Conf. Interval]*	
Decoupling index	5.9144	0.0000	0.1299	0.5953	−0.0392	0.5027

Table 7. The t-test of the decoupling index with the test value of zero.

Variable	*t*	*p*	*Std. Err.*	*Std. Dev.*	*[95% Conf. Interval]*	
Decoupling index	1.7838	0.0448	0.1299	0.5953	−0.0392	0.5027

However, several questions remain that we cannot currently thoroughly investigate. To be more specific, not all of the influencing factors can be analyzed due to the limitation of Kaya identity (must be divided into several multiplications). In this case, we can only select the key factors to carry out our study after a detailed review of the previous research that is related to similar topics. In future research, we will try to further our research by taking more spatial issues such as the spatial stratified heterogeneity phenomenon and spatial autocorrelation into consideration. Also, we will try to focus more on the provincial differences, the carbon emission mitigation performance, and responsibility allocation in future work.

4. Conclusions and Policy Implications

4.1. Conclusions

We analyzed the changes of five aspects of carbon dioxide emissions and decoupling status based on a historical trajectory of CO_2 emissions. Then, we carried out the decoupling index analysis deduced from the LMDI method to test whether the development of the electricity sector synchronized with the protection of the environment, and the degree to which the environment responded to the electricity sector output. Then, we compared the stability of the two indictors. Basically, the changes of the decoupling indicators are divided into five factors based on the LMDI approach to investigate the factors affecting the decoupling progress, and we arrived at some conclusions:

(1) The total CO_2 emissions from electricity generation increased while carbon intensity dropped in the study period; even some minor fluctuations were observed.

(2) In general, the electric output effect proved to be the dominant factor of CO_2 emission gains. In addition, the electricity intensity factor effect played a negative role in the decrease of carbon

dioxide emissions. The improvement of the energy conversion efficiency in electricity generation is beneficial for CO_2 emission reduction.

(3) Relative decoupling was the main state in the examined period; the expected strong decoupling was still not adequate. To be more specific, the strong decoupling state only occurred during 1997–1998, 2007–2008, and 2011–2012. However, no decoupling ruled the periods between 1994–1995, 1996–1997, 2001–2003, and 2010–2011. The electricity intensity effect and energy mix effect had positive impacts on accelerating the decoupling process in most of the observing years. Although the mission-factor effect did not show a relatively significant influence on decoupling, the decarbonization technology should not be ignored in the future.

(4) The elasticity tool had a more stable manifestation than the decoupling index, while the decoupling index identified and defined the decoupling status more systematically in China's electricity analysis.

4.2. Policy Implications

The emission reduction target of reducing the carbon intensity (carbon dioxide emissions per unit of GDP) to 40–45% of the value in 2005 was proposed at the Conference of the Parties held in Copenhagen in 2009 (COP15). In view of the actual situation, some recommendations are put forward to provide more information regarding policy development:

(1) Alongside rapid economic growth, the total demand for electricity is on the rise, since carbon emissions are generally considered to have a close relationship with thermal power plants. Measures that limit the thermal power plants increasing, and encourage them to improve their energy conversion technology should be encouraged. In consideration of the present situation, measures such as shutting down small thermal power units is an effective method. As is proposed by the National Development and Reform Commission (NDRC), if small thermal power units are all replaced by large units, the annual energy consumption of China can achieve a tangible saving of 90 million tons of standard coal. As a consequence, shutting down small thermal power units is of vital importance [59].

(2) Most of the thermal power plants in China generate energy by burning coal with high carbon content and low combustion efficiency, resulting in more CO_2 emissions. However, as far as the current situation is concerned, thermal power is still in the dominant position. Thus, the improvement of energy efficiency is treated as a key issue in reducing carbon emissions. Correspondingly, policies to improve energy conversion technologies and the renewable fuels should be valued. Moreover, developing a low-carbon economy and adjusting the industry structure are also sensible choices.

(3) Although the electricity power generation structure didn't seem to be the fundamental element affecting CO_2 emissions, upgrading the power generation structure can be a beneficial way to limit the growth of CO_2 emissions and diminish the harm to the environment. There is no doubt that fossil fuels consumed a large amount of energy in electricity generation; consequently, it is urgent to put measures that optimize the energy mix into practice. On the other hand, the proportion of coal-fired electricity generation still could not be brought under adequate control. Therefore, conventional power stations require more technology during the construction, which may make it possible to achieve the efficiency target of generating more electricity from less coal.

In sum, for China, it is more effective to shut down small thermal power units in the short term, but in the long run, focusing more on the technical improvements in fuel efficiency and adjusting the electricity production structure can bring considerable benefits to the electricity sector as well as the whole society.

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