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Decoupling and Decomposition Analysis of Carbon Emissions from Industry: A Case Study from China

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Abstract: China has overtaken the United States as the world's largest producer of carbon dioxide, with industrial carbon emissions (ICE) accounting for approximately 65% of the country's total emissions. Understanding the ICE decoupling patterns and factors influencing the decoupling status is a prerequisite for balancing economic growth and carbon emissions. This paper provides an overview of ICE based on decoupling elasticity and the Tapio decoupling model. Furthermore, the study identifies the factors contributing to ICE changes in China, using the Kaya identity and Log Mean Divisia Index (LMDI) techniques. Based on the effects and contributions of ICE, we close with a number of recommendations. The results revealed a significant upward trend of ICE during the study period 1994 to 2013, with a total amount of 11,147 million tons. Analyzing the decoupling relationship indicates that "weak decoupling" and "expansive decoupling" were the main states during the study period. The decomposition analysis showed that per capita wealth associated with industrial outputs and energy intensity are the main driving force of ICE, while energy intensity of industrial output and energy structure are major determinants for ICE reduction. The largest contributing cumulative effect to ICE is per capita wealth, at 1.23 in 2013. This factor is followed by energy intensity, with a contributing cumulative effect of −0.32. The cumulative effects of energy structure and population are relatively small, at 0.01 and 0.08, respectively.

Keywords: industrial carbon emissions (ICE); decomposition analysis; decoupling analysis; LMDI (Log Mean Divisia Index)

1. Introduction

A continuous growth in energy consumption has increased atmospheric carbon greenhouse gas emissions [1,2]. As a result, carbon currently contributes approximately 63% of the gaseous radiative force contributing to climate change. Atmospheric carbon had increased to 390.5 ppm by 2011, according to the IPCC reports [3–5], thus exceeding pre-industrial levels by approximately 40% [6]. China has surpassed the United States as the world's biggest carbon emitter. Industrial carbon emissions (ICE) accounted for approximately 65% of total emissions [7–9]. The increased ICE from China has received significant attention in light of global warming, and there is a global consensus about the importance of reducing greenhouse gas emissions. Reducing ICE has become increasingly important for the Chinese policymakers, partly because China committed itself to lower the carbon intensity of GDP by 40% to 45% below 2005 levels by 2020. Based on the Copenhagen Climate Change Conference in 2009 [10–14], China has realized the importance of reducing carbon emissions [15–18]. China also should pay significant attention to make emission reductions compatible with economic growth, especially for industry.

Past studies used decomposition methodologies to quantitatively identify factors on changes carbon emission, at country-, regional-, and global-level. These factors can in turn be applied in energy policymaking. For example, Shahbaz [19] and Leitão [20,21] discovered a relationship between the economy and carbon emissions from the perspective of globalization. Sun [22], Ma [23], Liao [24], Q. Wang [25], Paul [26], M. Shahbaz [27–30], and Lise [31] used a decomposition method to quantify the influencing factors of carbon emissions in China, India, Malaysia, Indonesia, Portugal, Turkey, and Brazil, respectively. Magazzino [18,32–35] used a time series approach to examine the relationship between GDP, energy consumption and carbon emissions, and energy use in the Gulf Cooperation Council countries, EMU countries, Israel, and ASEAN-6 countries.

Wang and Yang [36] used the Beijing–Tianjin–Hebei area as example to divide the literature about the relationship between ICE and economic growth into three assessment categories: energy efficiency, environment, and economic development. Using the DEA model, some studies measured environmental and energy performance in China [37–40] and conducted a comparative analysis of China's regional energy and emission performance [41]. Chung et al. [42] used the LMDI technique to evaluate the respective contributions of changes in residential energy use in Hong Kong. Leitão [43] used panel-data analysis to analyze energy consumption and foreign direct investment of Portugal. In general, researchers studying China have found that the decline in energy intensity has been the main factor associated with emissions deceleration [23,44–46]. Fan [47] uncovered that the change in primary energy-related carbon intensity and the material sectors' final energy-related carbon intensity mainly contributed to the decline in energy intensity.

In addition, other studies have compared energy-related carbon emissions between sectors, mostly concentrating on the rural energy and transport sectors. Wang [48] studied carbon emission from China's transport sector. Scholl [49] examined the five influencing factors on carbon emissions from passenger transport in nine OECD countries. Chipper [50] qualified the three key influencing factors on changes in energy use and carbon emissions from freight transport in 10 industrialized countries. Lakshmanan and Ha [51] reported that increased personal travel, population, and GDP contributed to changes in carbon emission from transport sector in the U.S. from 1970 to 1991

As mentioned above, previous studies usually focused two issues: (1) investigated the decoupling index of ICE and economic activities; and (2) assessed the status of decoupling. Few studies have researched the inner mechanisms of the changes of each factor. Furthermore, no research has been done on the decoupling and decomposition analysis of China's ICE using the most recent data. As the country with the most carbon emissions, China allows an effective case study for a decoupling, combine with decomposition technique. This paper is aimed to clarify the relationship between carbon emission and economic output in China's industrial sector, and then to examine these influencing factors of decoupling status. To achieve this, we developed a Tapio model based on extended Kaya identity to analysis decoupling status, and developed decoupling index based on LMDI techniques to study the contribution of different factors influencing industrial carbon emission in China from 1994–2013.

2. Data and Methodology

2.1. Data Sources

Data for the period of 1994 to 2013 were collected from issues of the China Statistical Yearbook [52–55]. The latest data are updated in the CSY-2015; industry has increased rapidly since 1994 and policy leaders have begun to pay greater attention to both energy efficiency and environmental pressure caused by ICE. China has begun to vigorously develop clean energies, such as wind power, photovoltaic, nuclear power, and shale gas [56–61] to reduce emissions. Despite this, however, 98% of industrial energy is coal consumption, which has constantly generated carbon emissions.

The National Bureau of Statistics of the People's Republic of China publishes the CSY yearly. It is the only official agency to publish statistical data; the data are comprehensive and highly reliability. In preparation for the decomposition analysis, data were specifically collected about energy consumption by industrial sector, which mainly includes coal consumption, coke consumption, crude oil consumption, gasoline consumption, kerosene consumption, diesel oil consumption, fuel oil consumption, and natural gas consumption. Industrial output and population data were also collected.

2.2. Logarithmic Mean Divisia Index (LMDI)

There are dozens of decomposition methods that enable analysts to identify the determinants of emissions changes over intervals of time. In general, studies have found that the LMDI is the most appropriate method to decompose energy consumption and emission changes [62–65]. Recently, the Logarithmic Mean Divisia Index (LMDI) approach to energy decomposition has emerged as a preferred decoupling model [66]. LMDI is a calculation process proven to be a complete decomposition method, without zero-value problems [67]. In this study, the decomposition technique was combined with a decoupling analysis to analyze the relationship between industrial growth and ICE. This allowed for the identification of factors that contribute to changes in China. The LMDI can be expressed as an extended Kaya identity, which was first proposed by Yoichi Kaya [68]. The extended Kaya identity is as follows:

$$\begin{aligned} C^t &= \sum_i^t C = \sum_i \frac{C_{it}}{E_{it}} \times \frac{E_{it}}{E_t} \times \frac{E_t}{IOV_t} \times \frac{IOV_t}{P_t} \times P_t \\ &= \sum_i^t r_{it} \times n_{it} \times e_t \times a_t \times P_t. \end{aligned} \tag{1}$$

In this expression, C^t represents the carbon emissions in the t year, the subscript i represents energy type; the superscript t represents year. The C_i^t is the carbon emissions of the ith energy in the t year; E_i^t is the consumption of the ith energy in the t year; E_t stands for total energy consumption in the t year; IOV_t denotes the industrial output values. Because the study's target period was 1994 to 2013, a more recent price index was considered more appropriate. As such, we used industrial output data adjusted to 1994 prices. Total energy consumption data were then converted into standard coal consumption. P_t represents the population in the t year. The $r_{it} = \frac{C_{it}}{E_{it}}$ denotes the carbon coefficient of ith energy, the $n_{it} = \frac{E_{it}}{E_t}$ illustrates the energy structure. The $e_t = \frac{E_t}{IOV_t}$ represents energy intensity, and the $a_t = \frac{IOV_t}{P_t}$ is the per capita wealth, reflecting the industrial scale.

According to the LMDI method, the change of carbon consumption between a base year 0 and a target year t, denoted by ΔC, is 0, because the carbon emission coefficients are basically unchanged and there is no systematic monitoring of ICE in China. Thus, ΔC can be decomposed into the following determinant factors:

$$\Delta C = \Delta C_n + \Delta C_e + \Delta C_a + \Delta C_p \tag{2}$$

where ΔC refers to the total changes in carbon emissions, which can be further decomposed into the following indictors: ΔC_n (the effect of energy structure), ΔC_e (the effect of energy intensity), ΔC_a (the effect of per capita wealth), ΔC_p (the population effect). If we measure the effects of determinant factors each year, we can generate figures for eight energy types. We can use the following formulae:

$$\Delta C_n = \sum_{i=1}^{8} L\left(C_i^{t-1}, C_i^t\right) In\left[\frac{n_i(t)}{n_i(t-1)}\right] \tag{3}$$

$$\Delta C_e = \sum_{i=1}^{8} L\left(C_i^{t-1}, C_i^t\right) In\left[\frac{e_i(t)}{e_i(t-1)}\right] \tag{4}$$

$$\Delta C_a = \sum_{i=1}^{8} L\left(C_i^{t-1}, C_i^t\right) In\left[\frac{a_i(t)}{a_i(t-1)}\right] \tag{5}$$

$$\Delta C_p = \sum_{i=1}^{8} L\left(C_i^{t-1}, C_i^t\right) In\left[\frac{p_i(t)}{p_i(t-1)}\right] \tag{6}$$

$$L\left(C_i^{t-1}, C_i^t\right) = \begin{cases} \frac{C_i^t - C_i^{t-1}}{In\left(C_i^t / C_i^{t-1}\right)}, C_i^t \neq C_i^{t-1} \\ C_i^t \text{ or } C_i^{t-1}, C_i^t = C_i^{t-1} \end{cases} \tag{7}$$

To measure the effect of each factor's contribution [11], we define them as follows:

$$G_n = \frac{\Delta C_n}{\Delta C} \tag{8}$$

$$G_e = \frac{\Delta C_e}{\Delta C} \tag{9}$$

$$G_a = \frac{\Delta C_a}{\Delta C} \tag{10}$$

$$G_p = \frac{\Delta C_p}{\Delta C} \tag{11}$$

where G_n, G_e, G_a and G_p indicate the effect of the contribution of energy structure, energy intensity, per capita wealth effect, and population, respectively.

2.3. Decoupling Elasticity Model

The decoupling model proposed by the Tapio model has been developed based on the OECD decoupling model, which has been widely used to analyze the relationship between economic growth and ICE [69–72]. The Tapio decoupling model does not require a base year, which is more efficient and appropriate than the OECD model [73], as it mitigates the problem of choosing a base period. To probe the decoupling status in a convenient and intuitive way, a novel decoupling index is needed. In this article, based on the additive decomposition results of energy-related CO_2 emission changes, the decoupling factor ε can be measured via the ratio defined by Tapio [74] as follows:

$$\varepsilon = \frac{\%C}{\%\mathrm{GDP}} = \frac{\Delta C/C}{\Delta \mathrm{GDP}/\mathrm{GDP}} = \frac{\left(\Delta C_n + \Delta C_e + \Delta C_a + \Delta C_p\right)/C}{\Delta \mathrm{GDP}/\mathrm{GDP}} \tag{12}$$

In this expression, ε is the decoupling factor, %C is the percent change in carbon emissions, and %GDP is the percent change of GDP. Carbon is the ICE for the current year, Δcarbon is the variation of ICE at the current time compared with the base period, GDP is the gross domestic product of the current year, and ΔGDP is the variation of gross domestic product at the current time compared with the base period. The results yielded eight logical possibilities, shown in Figure 1 [74]. These possibilities include weak decoupling, expansive decoupling, expansive negative decoupling, strong negative decoupling, weak negative decoupling, recessive coupling, recessive decoupling, and strong decoupling. These results are often named the environmental Kuznets curve (EKC) hypothesis [75,76].

According to the IPCC method of greenhouse gas emission inventories [68], carbon emissions can be estimated via the following formula:

$$C = \sum_i E_i \times r_i \sum_i E_i \times SC_i \times Q_i \times K_i. \tag{13}$$

In this formula, C represents carbon emissions, E_i is the ith energy consumption, and r_i ($kgCO_2/kg$ or $kgCO_2/m^3$) indicates the total energy consumption and the total CO_2 emission coefficient of ith energy. SC_i (tC/TJ) and O_i refer to the default value of carbon content and carbon oxidation rate; K_i (kJ/kg or kJ/m^3) indicates the average lower heating value (molecular weight of CO_2 divided by the molecular weight of carbon). Table 1 shows the default value of carbon content, carbon oxidation rate, average lower heating value, and carbon coefficient for different kinds of energy, based on the GHG Protocol Tool for Energy Consumption in China [77].

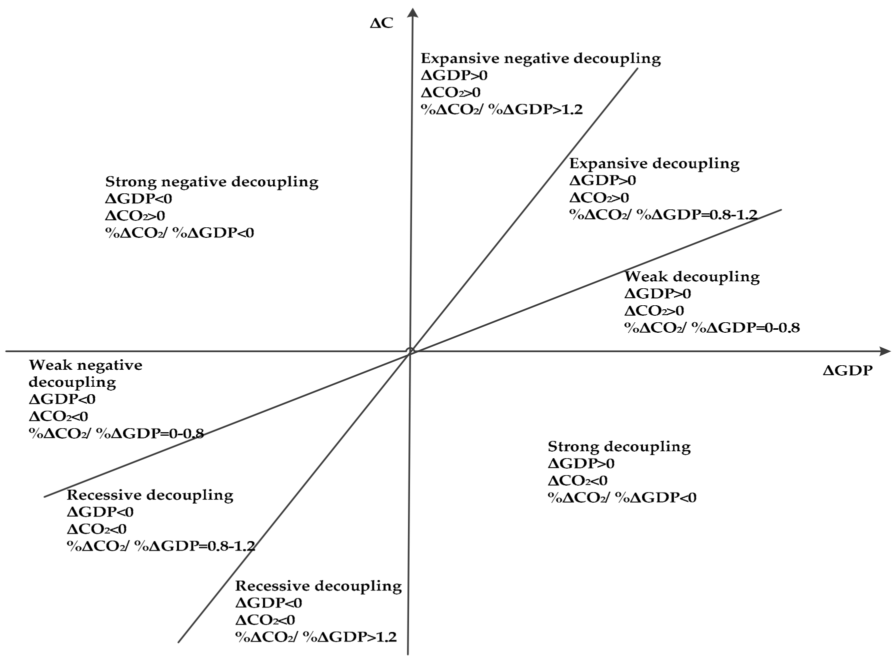

Figure 1. Decoupling between carbon emissions from industry and economic growth.

Table 1. The carbon coefficients of different kinds of energy.

Energy	Default Value of Carbon Content	Carbon Oxidation Rate	Average Lower Heating Value	Carbon Coefficient
	tC/TJ	%	kJ/kg or kJ/m^3	kgCO$_2$/kg or kgCO$_2$/m^3
Raw Coal	26.37	98%	20,908	1.981
Washed coal	25.41	98%	26,344	2.405
Other washed coal	25.41	98%	10,454	0.955
Coal products	33.6	98%	17,793	2.148
#: briquette	33.6	90%	17,584	1.950
coal water slurry	33.6	98%	19,854	2.397
Pulverized coal	33.6	98%	20,933	2.527
Coke	29.5	93%	28,435	2.860
Natural Gas	15.3	99%	389,310	21.622
Liquefied natural gas	15.3	100%	51,498	2.889
Crude Oil	20.1	98%	41,816	3.020
Gasoline	18.9	98%	43,070	2.925
Kerosene	19.6	98%	43,070	3.033
Diesel Oil	20.2	98%	42,652	3.096
Fuel Oil	21.1	98%	41,816	3.170
Liquefied petroleum gas	17.2	98%	50,179	3.101
Refinery Gas	18.2	98%	46,055	3.012
Other petroleum products	20.0	98%	35,168	2.527

3. Cointegration Test

Prior to the decoupling analysis, we conducted a comprehensive analysis of the stationary data and analyzed the long-run equilibrium relationship between total carbon dioxide emissions and the effect of each factor. This involved a cointegration test [78,79], where every independent variable was assessed in a one-to-one correspondence relationship with each of the effects listed above in the LMDI decomposition. CO_2 emissions was used as the dependent variable. We also conducted an Augmented Dickey–Fuller (ADF) Unite root test to assure the stationary property, subsequent to the Johansen System Cointegration Test.

3.1. Augmented Dickey–Fuller Unite Root Test

We applied the ADF Unite root test to conduct a stationary analysis of all variable quantities before the cointegration analysis. The variables (C, e, a, and p) were nondimensionalized before proceeding with ADF testing. Because there are eight kinds of energy, there are eight variables n_i $(i = 1, \ldots, 8)$; these are percentages and not nondimensionalized. Following the calculation, we analyzed the ADF test by comparing the calculated result and the hypothetical ADF value. If the critical value exceeded the ADF test value, then the result was considered stationary; if not, the testing result was considered nonstationary. Table 2 shows the ADF testing results; all the variables are stationary after logarithmic function and first and second differencing, suggesting that all the variables are integrated.

Table 2. ADF Unite root test.

Item		Test Value of ADF	Critical Value	Judging Conclusion
The logarithm	C	3.548228	−2.655194	Nonstationary
	e	−3.381739	−3.040391 **	Stationary
	a	−54.84574	−3.831511 ***	Stationary
	P	0.361199	−2.660551	Nonstationary
	n1	−0.926663	−2.655194	Nonstationary
	n2	−0.875207	−2.655194	Nonstationary
	n3	−2.292157	−2.666593	Nonstationary
	n4	−1.151329	−2.660551	Nonstationary
	n5	−1.003078	−2.660551	Nonstationary
	n6	−0.145338	−2.655194	Nonstationary
	n7	−0.718707	−2.655194	Nonstationary
	n8	1.657641	−2.655194	Nonstationary
First-order difference	C	−0.328314	−2.666593	Nonstationary
	P	−2.734556	−2.660551 *	Stationary
	n1	−2.335950	−2.660551	Nonstationary
	n2	−3.367909	−3.040391 **	Stationary
	n3	−2.330250	−2.660551	Nonstationary
	n4	−3.946359	−3.857386 ***	Stationary
	n5	−2.656369	−2.660551	Nonstationary
	n6	−4.781514	−3.857386 ***	Stationary
	n7	−3.861933	−3.857386 ***	Stationary
	n8	−3.124053	−3.040391 **	Stationary
Second-order difference	C	−4.264208	−3.886751 ***	Stationary
	n1	−4.958637	−3.886751 ***	Stationary
	n3	−5.720148	−3.886751 ***	Stationary
	n5	−5.429637	−3.886751 ***	Stationary

*, **, and *** indicate the effect is significant at the 10%, 5%, and 1% level.

3.2. Johansen System Cointegration Test

Based on unit root tests, the integrated data for the variables can be further tested for cointegration (Table 3). Table 3 shows the three cointegration relationships among the variables at the 1% level. In summary, the calculated results demonstrate that at least three cointegrating relationships exist between carbon dioxide emissions and energy intensity, per capita wealth, and population.

Table 3. The results of cointegration testing.

Hypothesized No. of CE(s)	Eigen Value	Trace Statistic	0.05 Critical Value	Prob. **
None *	0.957631	117.6483	47.85613	0.0000
At most 1 *	0.798904	60.74429	29.79707	0.0000
At most 2 *	0.745667	31.87281	15.49471	0.0001
At most 3 *	0.330752	7.228821	3.841466	0.0072

Trace test indicates at least three cointegrating equations at the 0.01 level; * denotes rejection of the hypothesis at the 0.01 level; ** MacKinnon, Haug, and Michelis (1999) *p*-values.

3.3. Descriptive Statistics and Correlation Analysis

Descriptive statistics are used to describe the basic features of the data in a study. Descriptive statistics usually include the measures of central tendency statistics, distributions of discrete variables statistics, and the degree of dispersion statistics. We use a data file containing data of 12 variables including C (total carbon emissions), P (the population), a (per capita wealth), e (energy intensity), and n_i (the percentage of consumption of the ith energy on the total energy consumption; there are eight kinds of energy, i = 1, 2, 3, . . . , 8) to conduct the descriptive statistics using SPSS version 2.0. The data are all metric data and time series data. The results of the descriptive statistics are presented below (Table 4). In the results of descriptive statistics, we use the index mean to measure the central tendency of variables, use the indexes Kurtosis and Skewness of variables to reflect the distributions of discrete variables, and use the indexes Standard deviation, Variance, Minimum, and Maximum to reflect the degree of dispersion.

Correlation analysis is useful for determining the direction and strength of a relationship between two variables. In the study, we also use a data file containing data on 12 variables including C, P (the population), a, e, and n_i (i = 1, 2, 3, . . . , 8) to conduct the descriptive statistics using SPSS version 2.0. The results of the correlation analysis are presented below (Table 5). The results of correlation analysis between different variables are shown in Table 5.

Table 4. Descriptive statistics on the variables.

	Mean	Standard Deviation	Variance	Kurtosis	Skewness	Minimum	Maximum	Confidence (95%)
C	563,331.074840	257,289.677671	66,197,978,236.160500	−0.785434	0.701214	300,319.042650	1,114,708.900140	120,415.275773
P	129,022.900000	4909.380483	24,102,016.726316	−0.951182	−0.357183	119,850.000000	136,072.000000	2297.660793
a	4749.559542	2662.863925	7,090,844.283580	−0.830278	0.673245	1621.293283	9971.630243	1246.258679
e	0.000381	0.000089	0.000000	0.832222	1.358377	0.000288	0.000591	0.000042
n1	0.653498	0.019937	0.000397	−0.212380	−0.776701	0.613648	0.682283	0.009331
n2	0.090363	0.013167	0.000173	−1.881357	0.245945	0.074478	0.109783	0.006163
n3	0.192158	0.020063	0.000403	−0.483370	0.716242	0.164170	0.231855	0.009390
n4	0.005366	0.002760	0.000008	−1.396561	0.382409	0.001825	0.010065	0.001292
n5	0.000472	0.000298	0.000000	−1.194223	0.470102	0.000096	0.000957	0.000140
n6	0.013423	0.003917	0.000015	−0.718475	−0.478773	0.005786	0.019091	0.001833
n7	0.023779	0.012010	0.000144	−1.675945	−0.129722	0.007278	0.041438	0.005621
n8	0.020943	0.005354	0.000029	0.119194	0.972847	0.014576	0.032483	0.002506

Table 5. Correlation analysis between different variables.

	P	a	e	n1	n2	n3	n4	n5	n6	n7	n8
CO_2	0.904 **	0.99 **	−0.666 **	0.505 *	0.901 **	−0.464 *	−0.876 **	−0.817 **	−0.914 **	−0.949 **	0.941 **
P		0.935 **	−0.909 **	0.142	0.858 **	−0.088	−0.968 **	−0.573 **	−0.716 **	−0.955 **	0.890 **
a			−0.743 **	0.397	0.876 **	−0.355	−0.886 **	−0.745 **	−0.880 **	−0.951 **	0.970 **
e				0.260	−0.628 **	−0.309	0.843 **	0.194	0.410	0.773 **	−0.744 **
n1					0.465 *	−0.982 **	−0.180	−0.838 **	−0.649 **	−0.380	0.280
n2						−0.469 **	−0.879 **	−0.808 **	−0.857 **	−0.935 **	0.789 **
n3							0.129	0.810 **	0.645 **	0.328	−0.256
n4								0.622 **	0.708 **	0.935 **	−0.816 **
n5									0.869 **	0.753 **	−0.629 **
n6										0.806 **	−0.844 **
n7											−0.870 **

** Significant correlation at the 0.01 level (two-tailed); * Significant correlation at the 0.05 level (two-tailed).

4. Analysis Results and Discussion

4.1. An Overview of Industrial Carbon Emissions

According to Equation (2), we first calculated carbon emissions from different energy types; we then calculated the industrial carbon emissions every year, shown in Table 6.

Table 6. The carbon emissions from different kinds of energy in the industrial sector in China.

Year	The Carbon Emissions from Different Kinds of Energy								Total
	Raw Coal	Coke	Crude Oil	Gasoline	Kerosene	Diesel Oil	Fuel Oil	Natural Gas	10 Thousand Tons
1994	213,492	25,174	42,180	2193	87	3404	10,556	3233	300,319
1995	232,908	29,778	44,443	2376	136	3684	10,798	3338	327,461
1996	245,418	30,005	47,386	2620	131	4202	10,165	3399	343,324
1997	241,030	30,271	51,937	2115	141	5357	10,217	3653	344,721
1998	227,721	30,632	52,012	1982	189	4167	10,199	3708	330,609
1999	223,372	28,861	56,701	1891	238	4665	9661	3896	329,285
2000	221,337	28,830	63,577	1761	255	4943	9431	4368	334,502
2001	225,057	30,426	63,928	1808	261	5070	9874	4709	341,134
2002	246,031	34,257	67,520	1849	265	5363	9354	4920	369,558
2003	298,276	40,469	74,801	1807	266	5667	10,261	5791	437,337
2004	356,848	48,566	86,449	1484	185	6207	11,318	6349	517,406
2005	401,042	62,808	90,477	1351	174	6475	9589	7650	579,565
2006	446,793	78,160	96,886	1370	146	6073	9624	8951	648,004
2007	485,885	86,035	102,281	1680	137	5334	8350	11,020	700,723
2008	526,102	85,104	106,704	1714	149	7793	6465	11,494	745,526
2009	554,459	90,786	114,685	1963	97	7272	4823	12,495	786,581
2010	586,439	96,049	129,004	2017	122	6699	7536	14,860	842,726
2011	646,262	108,829	132,459	1769	104	5648	7165	18,161	920,396
2012	665,051	112,291	140,610	1700	97	5411	7106	20,471	952,736
2013	798,654	130,685	146,480	1531	83	5189	7675	24,413	1,114,709

In addition, we used the carbon emission coefficients of different energy types based on the GHG Protocol Tool for Energy Consumption in China [77]. Figure 2 shows that the carbon emissions intensity could be analyzed in three stages: 1994–1997, 1998–1999, and 2000–2013. The ICE from industrial sectors experienced a significant upward trend during this period, reaching a total amount of 11,147 million tons in 2013. The ICE continuously increased, with the exception of 1998 and 1999. From 1994 to 1997, the ICE continued to steadily grow, with a rapid increase after 2000. The average annual growth rates of 1994–1997, 1998–1999, and 2000–2013 were 4.76%, −2.25%, and 9.23%, respectively. Due to the rapid economic growth, the ICE increased to 11,147 million tons by 2013, almost 3.7 times the 3003.19 million tons in 1994. In 1998–1999, the ICE decreased, falling across both years. This decline was mainly due to the Asian financial crisis in 1997, which affected China's economy. The slow industrial growth rate led to stable, low ICE in China.

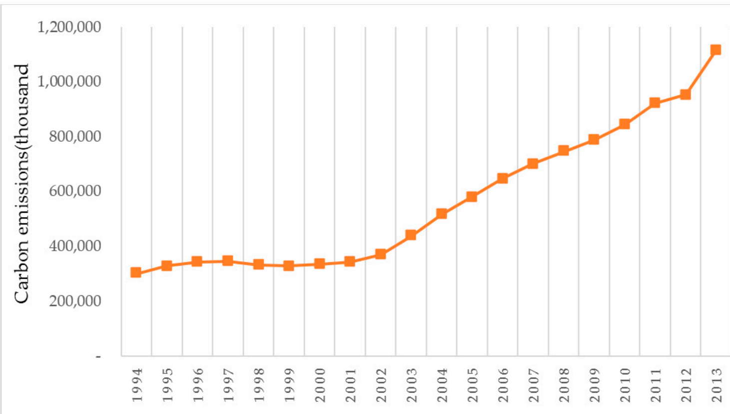

Figure 2. ICE from the industrial sector rose during the study period 1994–2013.

4.2. Decoupling Analysis

To explore the relationship between carbon emissions and economic growth, we used Equation (1) to calculate the decoupling elasticity using the IOV (Industrial Output Values) to replace economic growth. Table 1 shows the results; Figure 3 shows trends during the study period, comparing the environmental pressures posed by the industrial output values from 1995 to 2013. The specific values and status judgments related to decoupling elasticity are based on Figure 2 and the calculation process is shown in Table 1. Table 3 shows that the decoupling elasticity of the overall industrial sector can be divided into four states: weak decoupling, strong decoupling, expansive decoupling, and expansive negative decoupling. These coincide with Figure 3; for example, the values from 2003, 2004, and 2013 are higher in Figure 3. This indicates that the speed of ICE growth exceeded the speed of industrial output growth.

As Figure 3 and Table 6 show, the decoupling elasticity increased from 0.65 to 2.24, indicating that huge environmental pressure accompanied industrial growth. The trends associated with decoupling elasticity are different. The years 2003–2004 and 2013 were the most notable, as these years demonstrate a state of expansive negative decoupling. The decoupling elasticity values fluctuated between −0.05 and 1.6 except for 2013; the values reached their lowest points at −0.45999 and −0.0471 between 1998 and 1999. These reflect the best conditions and exert the least pressure on the environment with a minimal elasticity value, while maintaining an upward trend after 1999. Based on the decoupling analysis, the overall effect on industrial decoupling was still weak. Further, the decoupling relationship indicates that "weak decoupling" and "expansive decoupling" were the main states during the study period.

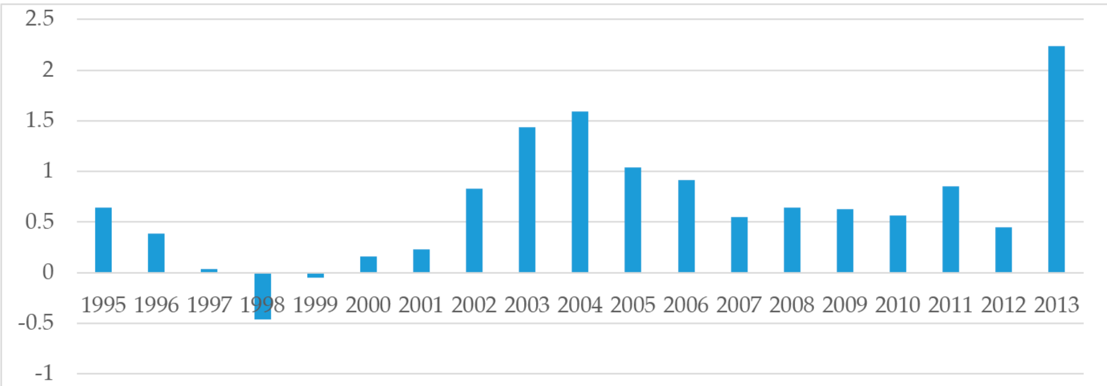

Figure 3. The decoupling elasticity of the industry sector during the period 1995–2013.

4.3. Decomposition Analysis

As discussed above, the decoupling analysis reflects the levels of environmental burden caused by the industrial sector. We use the decomposition technology proposed by the evaluation criterion to assesses industrial progress and identify the driving forces behind the increasing ICE [80,81]. Using LMDI, the ICE were decomposed into four effects (energy structure, energy intensity, per capita wealth effect, and population) to investigate the decoupling path of industry in China. The effects and cumulative effects indicate each factor's weight and the degree to which emission reduction efforts outweigh and define the contribution of industrial output. Tables 6 and 7 and Figure 4 present the results of the analysis. Table 2 shows the effects of different factors of ICE year by year from 1995 to 2013. In addition, we calculated the cumulative effects of different factors of ICE and the contributions of different factors, selecting 1984 as the base year. These are shown in Table 7 and Figure 4.

Table 7. The values of decoupling elasticity.

Year	ΔCarbon/Carbon	Δ*IOV*/*IOV*	ε	Status
1995	0.0904	0.1400	0.6456	weak decoupling
1996	0.0484	0.1250	0.3875	weak decoupling
1997	0.0041	0.1130	0.0360	weak decoupling
1998	−0.0409	0.0890	−0.4600	strong decoupling
1999	−0.0040	0.0850	−0.0471	strong decoupling
2000	0.0158	0.0980	0.1617	weak decoupling
2001	0.0198	0.0870	0.2279	weak decoupling
2002	0.0833	0.1000	0.8332	expansive decoupling
2003	0.1834	0.1280	1.4329	expansive negative decoupling
2004	0.1831	0.1150	1.5920	expansive negative decoupling
2005	0.1201	0.1160	1.0357	expansive decoupling
2006	0.1181	0.1290	0.9154	expansive decoupling
2007	0.0814	0.1490	0.5460	weak decoupling
2008	0.0639	0.0990	0.6458	weak decoupling
2009	0.0551	0.0880	0.6258	weak decoupling
2010	0.0714	0.1260	0.5665	weak decoupling
2011	0.0922	0.1080	0.8534	expansive decoupling
2012	0.0351	0.0790	0.4448	weak decoupling
2013	0.1700	0.0760	2.2369	expansive negative decoupling

A positive value indicates a positive influence on ICE increases; a negative value indicates a negative influence on ICE increases. As shown in Tables 6 and 7, different factors had different effects. Among the four factors, per capita wealth and energy intensity are the major factors influencing carbon emissions. Per capita wealth and population move in a consistent direction, and are always positive driving forces. Energy structure and energy intensity are mostly negative forces. Energy structure and population play a relatively unimportant role. To improve the accuracy of the results, we combined multiplicative decomposition with the calculation of effect contributions. The effects of different factors on ICE varied in China year by year are shown in Table 8.The results above suggest that both per capita wealth and population play a role in increasing carbon dioxide emissions. In contrast, the energy intensity varied from year to year, contributing to a decrease in carbon emissions. From the effect-level perspective, population effect and intensity effect contribute more to ICE, whereas energy structure and population are relatively weak. This is consistent with Figure 4. In terms of the contributions of different effects, the largest cumulative effect contribution of ICE is per capita wealth, which was 1.23 in 2013. This is followed by energy intensity, with a cumulative effect contribution of −0.32. The cumulative effect contribution of energy structure and population are relatively small, at 0.01 and 0.08, respectively.

The energy structure is the weakest factor contributing to ICE and fluctuates greatly from year to year. The effects of energy structure are negative from 1996 to 2000, and in 2009, 2010, and 2012; this indicates that the energy structure contributes to a decreased ICE. In other years, the effects caused by energy structure are positive; despite some fluctuations, energy structure effects generally rise, although they fluctuate. This caused the ICE to increase by 24.95 million tons in 2011 and 53.33 million tons in 2013. This relates to the increasing consumption ratio of energy emissions from carbon sources such as coal. Reducing the consumption of carbon-emitting energies such as coal is conducive to curbing ICE. In terms of effect contributions, the energy structure is the lowest factor. This finding confirms that China should further optimize its energy consumption structure to disincentive rapid ICE growth.

Energy intensity plays a negative role with respect to ICE. In other words, energy intensity helped decrease the ICE except in years 2003, 2004, and 2013. The cumulative effects caused by the energy intensity of industrial output rose from 1995 to 2012, causing the ICE to decline by 3369.08 million tons. When considering the effects caused by energy type, ICE increases in stage 1, decreases in stage 2, and then increases again. Despite the fluctuations, ICE rose overall, to an amount of 2299.52 million tons. We can see that the effects of energy intensity on the ICE steadily increased from 1995 to 1998 and from 2004 to 2007, and declined during 1998–2004. The level fluctuated between 2007 and 2013.

Table 8. The effects of different factors on ICE varied in China year by year.

Year	ΔCn	ΔCe	ΔCa	ΔCp	ΔC
1995	816.7404	−14,773.8911	37,790.6448	3308.9264	27,142.4205
1996	−111.6941	−23,519.3564	36,001.9293	3492.0859	15,862.9648
1997	−1538.3893	−33,887.4333	33,363.8140	3458.8655	1396.8570
1998	−492.9173	−42,401.3066	25,696.4680	3085.1055	−14,112.6504
1999	−1647.0613	−26,588.8563	24,213.0779	2699.1920	−1323.6478
2000	−1876.3224	−23,928.6216	28,506.9082	2514.9781	5216.9423
2001	113.2695	−21,661.2785	25,832.0187	2347.8982	6631.9079
2002	1024.6759	−6448.5367	31,556.6245	2290.9983	28,423.7621
2003	1885.9979	17,421.3899	46,054.8216	2417.6521	67,779.8615
2004	1405.2259	26,825.5620	49,041.3097	2796.1024	80,068.2000
2005	2894.1806	−844.2010	56,883.0005	3226.3559	62,159.3360
2006	2048.6282	−7,990.7085	71,145.3674	3235.8213	68,439.1083
2007	859.7207	−41,745.6533	90,122.1957	3482.4987	52,718.7618
2008	379.9409	−23,801.8453	64,553.6203	3671.8475	44,803.5634
2009	−46.8693	−23,487.1678	60,860.5609	3727.5735	41,054.0972
2010	−2770.9293	−37,706.3690	92,720.8006	3901.4788	56,144.9810
2011	2495.6581	−15,163.4641	86,117.7331	4220.3934	77,670.3205
2012	−1655.7798	−37,206.5149	66,564.2360	4638.2381	32,340.1793
2013	5333.7840	81,090.8460	70,472.6315	5075.6306	161,972.8921

Accumulated effects of different factors on ICE from industry varied in China are shown in Table 9.The cumulative effects of per capita wealth and population are positive values and contribute to the increase of ICE every year. Per capita wealth is rising by year, and the contribution of this factor is also the largest. This indicates that the increase in per capita wealth is the most important factor driving ICE increase. From 1995 to 2014, the effects of per capita wealth vary every year. In the first phase, from 1995 to 1999, the effects of per capita wealth declined steadily, dropping to the lowest point of 24,213 million tons in 1999. The Asian financial crisis in 1997 led to a decline in industrial output, leading to the low contribution of ICE in China. In the second phase, from 2000 to 2011, the overall trend was stable within a specific range of fluctuations. In the third phase, there was a rapid increase during the investigated period, with the contribution reaching the highest point of 901.22 million tons in 2007. In the fourth phase, from 2008 to 2013, the carbon emissions fluctuated, but rose overall, maintaining a high contribution level. The average contribution is up to 735.48 million tons.

However, population did not significantly impact carbon dioxide emissions, even though it did contribute to increased emissions. The cumulative contribution of the population effect is very small, indicating that increased population affected ICE only weakly. The cumulative contribution of population to ICE changed only slightly, with an initial increase of 33.08 million tons in 1995. Throughout the study period, the carbon dioxide emissions decreased by 635.91 million tons in 2013.

Figure 4 shows the factors' contributions and effects more intuitively. The trends are consistent with Tables 6 and 7. The largest contributing cumulative effect on ICE is per capita wealth, which was 1.23 in 2013. This was followed by energy intensity, with a cumulative effect contribution of −0.32. The cumulative effect contribution of energy structure and population are relatively small, at 0.01 and 0.08, respectively. Industrial output was the main driving force behind ICE. This factor and the relatively high energy intensity caused the increase during this period.

Table 9. Accumulated effects of different factors on ICE varied in China.

Year	ΔCn	ΔCe	ΔCa	ΔCp	ΔC
1995	816.7404	−14,773.9	37,790.64	3308.926	27,142.42
1996	705.0464	−38,293.2	73,792.57	6801.012	43,005.39
1997	−833.343	−72,180.7	107,156.4	10,259.88	44,402.24
1998	−1326.26	−114,582	132,852.9	13,344.98	30,289.59
1999	−2973.32	−141,171	157,065.9	16,044.18	28,965.94
2000	−4849.64	−165,099	185,572.8	18,559.15	34,182.89
2001	−4736.37	−186,761	211,404.9	20,907.05	40,814.79
2002	−3711.7	−193,209	242,961.5	23,198.05	69,238.56
2003	−1825.7	−175,788	289,016.3	25,615.7	137,018.4
2004	−420.475	−148,962	338,057.6	28,411.8	217,086.6
2005	2473.706	−149,807	394,940.6	31,638.16	279,246
2006	4522.334	−157,797	466,086	34,873.98	347,685.1
2007	5382.055	−199,543	556,208.2	38,356.48	400,403.8
2008	5761.996	−223,345	620,761.8	42,028.33	445,207.4
2009	5715.126	−246,832	681,622.4	45,755.9	486,261.5
2010	2944.197	−284,538	774,343.2	49,657.38	542,406.5
2011	5439.855	−299,702	860,460.9	53,877.77	620,076.8
2012	3784.075	−336,908	927,025.1	58,516.01	652,417
2013	9117.859	−255,817	997,497.8	63,591.64	814,389.9

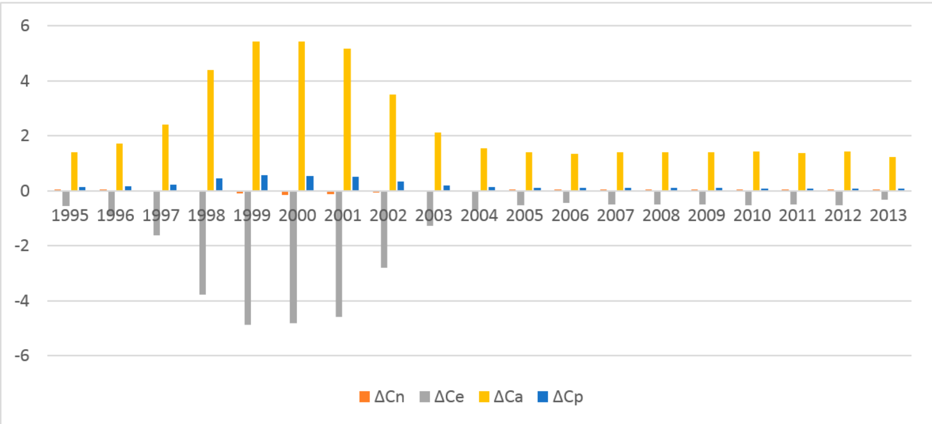

Figure 4. The contributions of different factors on ICE varied in China year by year.

5. Conclusions

This study analyzed data from 1994 to 2013 to provide an overview of industrial carbon emissions, based on decoupling elasticity and using a Tapio decoupling model. The Kaya identity and LMDI (Log Mean Divisia Index) methods were used to identify the factors contributing to changes in China's industrial carbon emissions. We also evaluated the accumulated effects and the contributions on ICE. Conclusions were developed based on the decoupling analysis and decomposition analysis. Proposals are made to curb the growth of carbon emissions and to balance economic development and environmental protection.

ICE from industrial sectors revealed a significant upward trend during the study period, reaching an amount of 11,147 million tons in 2013. The average annual growth rates for 1994–1997, 1998–1999, and 2000–2013 were 4.76%, −2.25%, and 9.23%, respectively. The stable low level of ICE in China can be mainly explained by the Asian financial crisis in 1997, which impacted China's economy and resulted in a slow industrial growth rate in China.

When considering the decoupling relationship, "weak decoupling" and "expansive decoupling" were the main states during the studied period. The decoupling elasticity experienced an increasing trend from 0.65 to 2.24. This indicates that industrial growth was accompanied by significant pressure on the environment. Based on the decoupling analysis, the overall effect on industrial decoupling was still weak.

The per capita wealth of industrial output and energy intensity are major factors that influence carbon emissions. The per capita wealth of industrial output and population move in a consistent direction, and are always positive driving forces. By contrast, energy structure and energy intensity are mostly negative forces. Energy structure and population play a relatively unimportant role. In terms of contribution effects, the largest cumulative effect on ICE is per capita wealth, which was 1.23 in 2013. This factor is followed by energy intensity, with a cumulative contribution of −0.32. The cumulative contributions of energy structure and population are relatively small, at 0.01 and 0.08, respectively.

In conclusion, some critical approaches to reducing carbon emissions are to further expand industrial scales and improve industrial output. In addition, vigorously promoting optimization, upgrading traditionally high energy consuming enterprises, and cluster development may help inhibit carbon emissions growth. The energy intensity factor has been diminishing, resulting in a relative slow-down in the decrease of emissions. When compared with some developed countries, China's energy intensity with respect to industrial output remains high. New strategies and increased efforts are needed to improve management and technological practices that will reduce energy intensity. Other approaches, such as further improving thermal power technologies and clean electricity, may also reduce carbon emission coefficients. The fastest way to significantly reduce carbon emissions in the short term is to adjust energy structures and optimize a sustainable energy consumption structure.

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Author Contributions: Qiang Wang conceived and designed the experiments and wrote the paper; Rongrong Li performed the experiments, analyzed the data, and contributed reagents/materials/analysis tools. All authors read and approved the final manuscript.

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