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Study on industrial carbon emissions in China based on GDIM decomposition method and two decoupling effects

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Abstract: The driving factors of China's industrial carbon emissions are decomposed by GDIM, so as to explore the reasons for the change of China's industrial carbon emissions. The decoupling effect of China's industrial carbon emissions and economic growth is studied by speed decoupling and quantity decoupling. The speed decoupling is measured by Tapio decoupling elasticity and emission reduction effort function, and the quantity decoupling is measured by environmental Kuznets curve (EKC). The results show that the positive driving factors are output size effect > industrial energy consumption effect > population size effect, and the negative driving factors are investment carbon emission effect > output carbon intensity effect > per capita output effect > economic efficiency effect > energy intensity effect. The elasticity of emission reduction is basically greater than that of energy conservation, indicating that there is still much room for efforts in emission reduction. The overall decoupling effect of carbon emissions is undecoupling - strong decoupling - undecoupling. The shape of quadratic EKC curve is "U" type, and the shape of cubic EKC curve is "N" type, which satisfies the EKC curve hypothesis.

Key words: Carbon emission; Decoupling effect; Generalized Dee index decomposition method (GDIM); Environmental Kuznets curve (EKC); Chinese industry

1 Introduction

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Since 1990, human activities have gradually increased climate warming. Our country in 1994 discovered the energy shortage, nervous use of energy, as well as high energy consumption and high emissions caused by the traditional fossil energy sources, and began to enhance the energy efficiency and adjust the energy structure. Since 2007, renewable energy sources have been developed and utilized to further optimize the energy mix, and low-carbon technologies have been encouraged to improve emission reduction efficiency. In 2016, the low-carbon development goals and tasks were detailed, indicating that the goal is to achieve carbon peak around 2030 and carbon neutrality around 2060. And with the rapid development of Chinese economy, the relationship between carbon emission and economic growth needs to be studied. It is also important to realize the decoupling of both as soon as possible.

Many scholars have studied the influencing factors of carbon emission, and the decomposition method used is mainly factor decomposition analysis (DA), which mainly includes structure decomposition analysis (SDA) and index decomposition analysis (IDA)(Hoekstra R 2003). The structural decomposition analysis method mainly relies on the consumption coefficient matrix, and quantitatively analyzes various direct or indirect influencing factors by using input-output table, including input-output method and two-stage decomposition method(Su B 2012); The index decomposition analysis method decomposed the change of a target variable into the product of several different factors, and found out the contribution rate of each influencing factor according to different methods to determine the weight, so as to separate the influence of each influencing factor on the target variable, including the Laspeyres index decomposition and Divisia index decomposition(Ang B W 2000). Laspeyres index decomposition method will produce large residual value in decomposition, thus forming a large error. Divisia index decomposition method main When there is a “0” or negative value in the data, the calculation of the average weight will face obstacles and become unworkable. Therefore, Ang and Choi, Ang and Liu improved the index decomposition method (IDA), that is, replace the exponent with logarithm, and use the "small value replacement method" to deal with the “0” value problem in the decomposition operation. Logarithmic mean Dee index decomposition method (LMDI) is proposed, which has the advantages of eliminating residual term, time independence, effective handling of zero value and consistency of data collection(Ang B W 1997 2007).

With the continuous application of logarithmic mean Dee index decomposition method (LMDI), its shortcomings gradually appear. Vaninsky pointed out that index decomposition methods decompose target variables into the form of product of multiple influencing factors based on the identity of Kaya(Kaya Y 1989), so that each factor has an interdependent relationship in form, and the selection of factors determines the decomposition results. When different influencing factors are selected for the same target variable to decompose, contradictory conclusions may be obtained. Therefore, Vaninsky proposed a generalized Dee index decomposition (GDIM)(Vaninsky A 2014), which is based on the exponential decomposition method and overcomes the shortcomings of the method. Therefore, it can analyze the influencing factors of China's industrial carbon emissions more comprehensively and accurately. This method has been applied to mining industry(Shao S 2016), transportation industry(Wang Y 2018) and electric power industry(Zhu L 2018). Shao S et al(2017), Li Z G et al(2019), Yan Q Y et al(2017) used GDIM decomposition method to analyze the influencing factors of carbon emission. In this paper, GDIM method is used to analyze and study the driving factors of carbon emission in the past 20 years.

The ideal relationship between carbon emissions and economic growth is decoupling. Decoupling theory is a basic theory proposed by the Organization for Economic Cooperation and Development (OECD) to describe the blocking of the link between economic growth and resource consumption or environmental pollution. Economic growth will lead to the increase of resource consumption and environmental pressure, but when the policy measures taken or the new technology adopted are effective, the same or even faster economic growth may be achieved with lower energy consumption or less environmental pressure. This process is called decoupling. Decoupling of carbon emissions is an idealized process in which the relationship between economic growth and greenhouse gas emissions continues to weaken or even disappear. In other words, energy consumption is gradually reduced on the basis of economic growth. Therefore, decoupling elasticity of carbon emissions becomes the main tool to measure the low-carbon status of each region.

Decoupling theory has been widely used to study the relationship between economic growth and carbon emissions(Chen J 2018, Hossain M A 2022, Wu Y 2019), mainly including OECD(2002) decoupling index model and Tapio decoupling state analysis model. OECD decoupling index is mainly used to describe the relationship between environmental pressure and driving force, which can be divided into “relative decoupling” and “absolute decoupling”. The Tapio decoupling state analysis model is a decoupling index calculation formula proposed by Tapio(2005) when studying the relationship between economic growth and carbon emissions, and the classification is more detailed. Thus, this paper also applies the Tapio model to analyze the speed decoupling effect. Environmental Kuznets Curve (EKC) is a tool proposed by Grossman et al. to study the relationship between environmental quality and economic growth, and it is believed that environmental pollution and per capita income show an inverted “U” shape. Subsequently, EKC model has been widely studied, and it is believed that there is not only inverted “U” type(Roberts J T 1997, Galeotti M 2006), but also linear(Wagner M 2008, Shafik N 1994) and “N” type(Glaser M 2003, Martinez-Zarzoso I 2004). The EKC model can be regarded as a research method of quantitative decoupling(Xiao J C 2022), and combined with the analysis of speed decoupling, to understand the decoupling between carbon emissions and economic growth from various aspects.

This paper elaborates from four parts. In the first part, the author states what problem to study and the research status of domestic and foreign scholars. The second part introduces the theory and method used in this paper in detail; The third part is the empirical analysis of the decomposition of driving factors of China's industrial carbon emissions and the decoupling effect from economic growth. The fourth part is the prospect. The specific research ideas are shown in Figure 1.

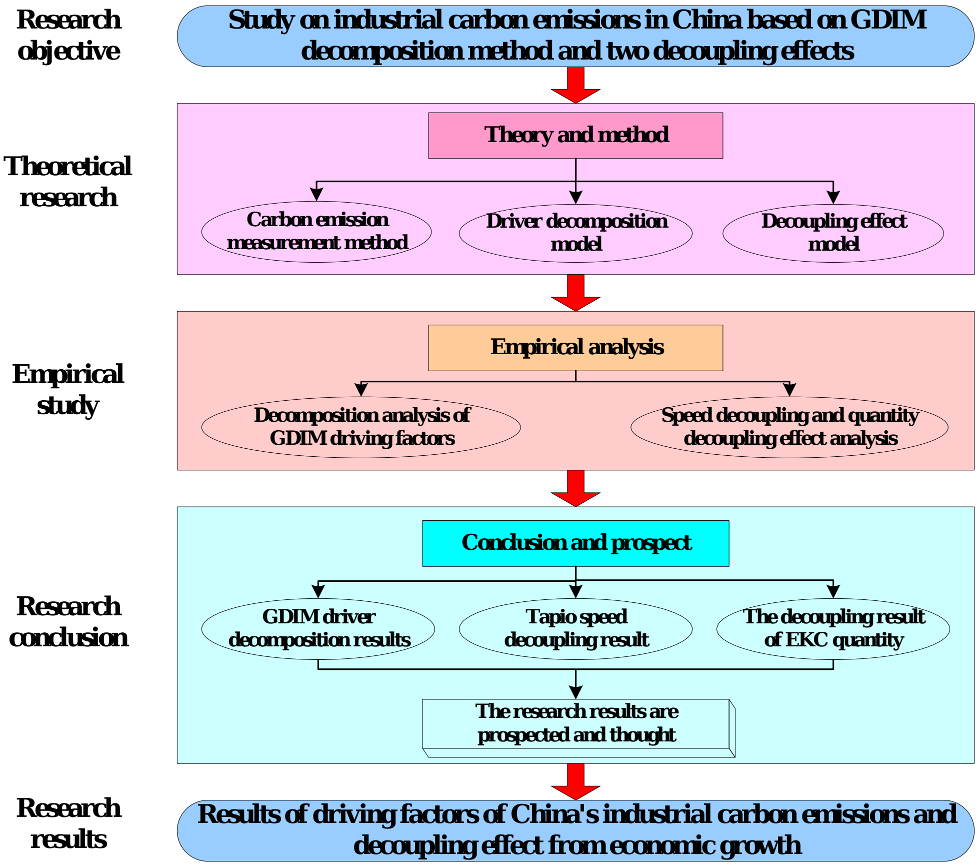


Figure 1　Overall research idea

2 Theory and Method

2.1 Research Framework

The specific research framework of this section is shown in Figure 2.

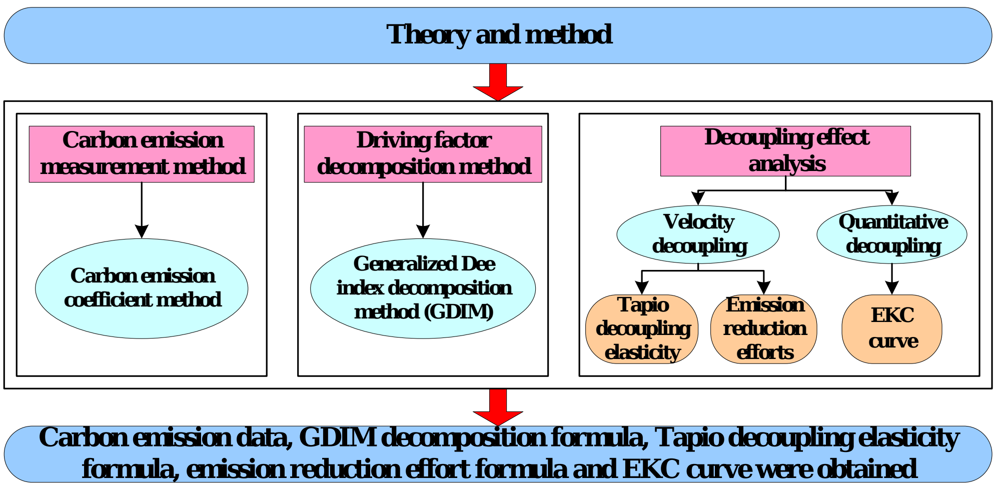


Figure 2　Research framework of theory and method

2.2 Measurement of Carbon Emissions

Carbon emissions are mainly generated by the combustion of fossil fuels, mainly from raw coal, coke, crude oil, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas and natural gas. This paper will calculate carbon emissions through these nine energy sources. Electricity was not taken into account to prevent double counting(Ye Y A 2013). The calculation method is carbon emission calculation method proposed by IPCC Guidelines for National Greenhouse Gas Inventories established by the United Nations, which is called carbon emission coefficient method. The specific formula for calculating carbon emissions from China's industrial sector is as follows:

$$C = \sum_i E_i \times NCV_i \times CEF_i \times COF_i \times \frac{44}{12}$$

Where: C represents carbon dioxide emissions, and the unit is 10,000 tons of standard coal; E_i represents the consumption of fossil energy of the i type, and the unit is generally 10,000 tons or 100 million cubic meters. NCV_i represents the average low calorific value of the i fossil energy, expressed in KJ/kg or KJ/m^3; CEF_i represents the carbon content per unit heat of the i fossil energy, and the unit is tC/GJ; COF_i is the carbon oxidation rate of the i fossil energy and the unit is %; 44/12 is the molecular weight ratio of CO_2 to C. The discounted coal coefficient, average low calorific value, carbon content per unit heat, carbon oxidation rate and carbon emission coefficient of these nine fossil energy sources are shown in Table 1.

The calculation formula of carbon emission coefficient is as follows:

$$C_i = NCV_i \times CEF_i \times COF_i \times \frac{44}{12} \div (CF_i \times a)$$

Where: C_i represents carbon dioxide emission coefficient; CF_i represents the conversion coefficient of the i fossil energy; a represents the conversion factor between grams and tons. The size is 1×10^{-6}; The meanings of NCV_i, COF_i, CEF_i and 44/12 are the same as those in the preceding paragraph, so they are not repeated.

Table 1 Emission coefficient of nine fossil energy sources

Energy type	Coefficient of discount coal (kg standard coal /kg)	Average low calorific value (KJ/kg)	Carbon per unit of heat (tC/TJ)	Carbon oxidation rate (%)	CO_2 emission coefficient (t/tce)
Raw coal	0.71	20908	26.37	94	2.66
coke	0.97	28435	29.42	93	2.94
Crude oil	1.43	41816	20.08	98	2.11
gasoline	1.47	43070	18.90	98	1.99
kerosene	1.47	43070	15.30	98	1.61
Diesel oil	1.46	42652	20.20	98	2.13
Fuel oil	1.43	41816	21.10	98	2.22
Liquefied petroleum gas	1.71	50179	17.20	98	1.81
Natural gas	13.30	38931	15.32	99	0.16

Data source: In the 2006 IPCC Guidelines for National Greenhouse Gas Inventories, China Energy Statistical Yearbook and China Greenhouse Gas Inventory Study, the discounted coal coefficient and carbon emission coefficient are kept as two decimal places.

2.3 Driver Decomposition Model

GDIM is a multi-factor decomposition model established on the basis of Kaya identity, which is used to decompose the driving factors of carbon emissions and explore the causes of carbon emission changes. Based on the GDIM principle, the expression of the improved GDIM mathematical model for industrial carbon emissions is as follows:

$$CO_2 = \frac{CO_2}{GDP} \times GDP = \frac{CO_2}{E} \times E = \frac{CO_2}{I} \times I = \frac{CO_2}{P} \times P = \frac{CO_2}{T} \times T$$

$$\frac{GDP}{P} = \frac{CO_2}{P} / \frac{CO_2}{GDP}$$

$$\frac{E}{GDP} = \frac{CO_2}{GDP} / \frac{CO_2}{E}$$

Table 2 Setting and explanation of different indicators

indicators	Set variables	Indicator meaning	Index unit
CO_2	C	Carbon emission	Ten thousand tons
GDP	X_1	Industrial output	Hundred million yuan
CO_2 / GDP	X_2	Produced carbon intensity	Tons per billion yuan
E	X_3	Industrial energy consumption	Ten kiloton standard coal
CO_2 / E	X_4	Carbon intensity of energy consumption	Tons/ton standard coal
I	X_5	Amount of industrial investment	Hundred million yuan
CO_2 / I	X_6	Investment carbon emission	Ton/ten thousand yuan
P	X_7	Population size	Ten thousand people
CO_2 / P	X_8	Per capita carbon emissions	Ton/person
T	X_9	Industrial technological progress	Hundred million yuan
CO_2 / T	X_{10}	Carbon intensity of technological progress	Ton/ten thousand yuan
GDP / P	X_{11}	Output per capita	10,000 yuan/person
E / GDP	X_{12}	Energy intensity	Tons of standard coal/ten thousand yuan
I / GDP	X_{13}	Economic efficiency	%

Note: The index of industrial technological progress was converted into the constant price in 2000 by “0.55* consumer price index +0.45* fixed asset investment price index”(Zhu P F 2003), and the data came from China Statistical Yearbook of Science and Technology.

The identity can become:

$$C = X_1 X_2 = X_3 X_4 = X_5 X_6 = X_7 X_8 = X_9 X_{10}$$

$$X_{11} = \frac{X_8}{X_2}$$

$$X_{12} = \frac{X_2}{X_4}$$

$$X_{13} = \frac{X_2}{X_6}$$

In order to apply GDIM decomposition method, the above formula is further converted into the following form:

$$Z = X_1 X_2$$
$$X_1 X_2 - X_3 X_4 = 0$$
$$X_1 X_2 - X_5 X_6 = 0$$
$$X_1 X_2 - X_7 X_8 = 0$$
$$X_1 X_2 - X_9 X_{10} = 0$$
$$X_8 - X_2 X_{11} = 0$$
$$X_2 - X_4 X_{12} = 0$$
$$X_2 - X_6 X_{13} = 0$$

According to the above formula, the gradient function of contribution $C(X)$ of influencing factors of carbon emission and the Jacobian matrix are constructed as follows:

$$\nabla C = (X_2, X_1, 0,0,0,0,0,0,0,0,0,0,0)^T$$

$$\Phi_X = \begin{pmatrix} X_2 & X_1 & -X_4 & -X_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ X_2 & X_1 & 0 & 0 & -X_6 & -X_5 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ X_2 & X_1 & 0 & 0 & 0 & 0 & -X_8 & -X_7 & 0 & 0 & 0 & 0 & 0 \\ X_2 & X_1 & 0 & 0 & 0 & 0 & 0 & 0 & -X_{10} & -X_9 & 0 & 0 & 0 \\ 0 & -X_{11} & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 & -X_2 & 0 & 0 \\ 0 & 1 & 0 & -X_{12} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & -X_4 & 0 \\ 0 & 1 & 0 & 0 & 0 & -X_{13} & 0 & 0 & 0 & 0 & 0 & 0 & -X_6 \end{pmatrix}$$

Decomposition vector: $\Delta Z[X|\Phi] = \int_L \nabla Z^T (I - \Phi_X \Phi_X^+) dX$

Where, $f(X_1, X_2, \cdots, X_{13}) = 0$, the vector is of form $\Phi(X) = 0$. I is the identity matrix, Φ_X is the Jacobian of $\Phi(X)$, Φ_X^+ is the generalized inverse of Φ_X, $\Phi_X^+ = (\Phi_X^T \Phi_X)^{-1} \Phi_X^T$.

Therefore, the driving factors of industrial carbon emissions are decomposed into the sum of 13 factors, including five absolute factors and eight relative factors. Absolute influencing factors ΔC_{X1}, ΔC_{X3}, ΔC_{X5}, ΔC_{X7} and ΔC_{X9} are respectively the influence of output scale change, energy consumption scale change, population scale change, industrial investment change and technological progress change on industrial carbon emission change. Relative influencing factors ΔC_{X2}, ΔC_{X4}, ΔC_{X6}, ΔC_{X8}, ΔC_{X10}, ΔC_{X11}, ΔC_{X12} and ΔC_{X13} respectively represent the influence of changes in carbon intensity of industrial development, industrial energy consumption intensity, investment carbon emission, per capita carbon emission, technological progress carbon intensity, per capita industrial added value, energy intensity and economic efficiency on changes in industrial carbon emission.

2.3 Decoupling Effect

2.3.1 Velocity Decoupling

(1) Tapio Decoupling Elasticity Index

OECD decoupling index divides decoupling types easily, while Tapio decoupling index divides them more finely. Based on an elastic analysis, decoupling index can be selected more flexibly in time and has no influence on different dimensions, so the calculation results are more stable. This paper uses the Tapio decoupling index to explore the unbalanced relationship between economic growth and carbon emissions. The decoupling index of carbon emissions and economic growth refers to the ratio of the rate of change of carbon emissions to the rate of change of GDP in a certain period of time. The expression is:

$$\varepsilon = \frac{\Delta C / C}{\Delta GDP / GDP}$$

Where, ε represents the decoupling elasticity index, and ΔC and ΔGDP respectively represent the change amount of carbon emission and industrial output value from the base year to the t year. C and GDP represent carbon emissions and industrial output value in the base period. Based on this theory, ΔC is decomposed and the following formula is obtained:

$$\varepsilon = \frac{\Delta C_{X1} + \Delta C_{X2} + \Delta C_{X3} + \Delta C_{X4} + \Delta C_{X5} + \Delta C_{X6} + \Delta C_{X7} + \Delta C_{X8} + \Delta C_{X9} + \Delta C_{X10} + \Delta C_{X11} + \Delta C_{X12} + \Delta C_{X13} / C}{\Delta GDP / GDP}$$

$$\varepsilon = \varepsilon_1 + \varepsilon_2 + \varepsilon_3 + \varepsilon_4 + \varepsilon_5 + \varepsilon_6 + \varepsilon_7 + \varepsilon_8 + \varepsilon_9 + \varepsilon_{10} + \varepsilon_{11} + \varepsilon_{12} + \varepsilon_{13}$$

Where $\varepsilon, \varepsilon_1, \ldots, \varepsilon_{13}$ respectively represents the decoupling elasticity of carbon emissions, gross industrial product, carbon intensity of output, industrial energy consumption, carbon intensity of energy consumption, industrial investment volume, carbon emission of investment, population size, carbon emission per capita, industrial technological progress, carbon intensity of technological progress, per capita Decoupling elasticity of industrial added value, energy intensity and economic efficiency.

$\varepsilon_{14} = \frac{\Delta CO_2 / CO_2}{\Delta E / E}$ is the elasticity of emission reduction and decoupling, indicating the industrial energy structure; $\varepsilon_3 = \frac{\Delta E / E}{\Delta GDP / GDP}$ is the decoupling elasticity of output carbon intensity, which can also be understood as the decoupling elasticity of energy conservation and the efficiency of industrial energy use.

Table 3 Judgment of decoupling state

Decoupling condition		ΔCO_2	ΔGDP	elasticity ε	meaning
Negative decoupling	Expansion negative decoupling	>0	>0	$\varepsilon > 1.2$	Both economic growth and carbon emissions are rising, with carbon emissions growing faster than economic growth
	Strong negative decoupling	>0	<0	$\varepsilon < 0$	Carbon emissions are rising and economic growth is negative
	Weak negative decoupling	<0	<0	$0 \le \varepsilon < 0.8$	Carbon emissions and economic growth are both negative, and carbon emissions deceleration is less than economic deceleration
decoupling	Weak decoupling	>0	>0	$0 \le \varepsilon < 0.8$	Economic growth is faster than carbon emissions
	Strong decoupling	<0	>0	$\varepsilon < 0$	The economy is growing and carbon emissions are falling
	Recessionary decoupling	<0	<0	$\varepsilon > 1.2$	Both the economy and carbon emissions are growing negatively, and the deceleration of carbon emissions is greater than that of the economy
connection	Expansion decoupling	>0	>0	$0.8 \le \varepsilon < 1.2$	Both the economy and carbon emissions are growing, with relatively small differences
	Recessionary decoupling	<0	<0	$0.8 \le \varepsilon < 1.2$	Economic growth and carbon emissions are both negative, the deceleration difference is small

Among them, the decoupling effect is the most ideal state for strong decoupling, because at the same time of economic growth, carbon emissions are reducing, indicating that the economic growth got rid of the dependence of carbon emissions.

(2) Emission Reduction Efforts

Diakoulaki et al (Diakoulaki D 2007) defined the government's emission reduction efforts as policies or measures taken to directly or indirectly reduce carbon emissions. In this paper, a emission reduction effort model was built based on DPSIR framework.

$$\Delta F = \Delta C - \Delta C_{X1} = \Delta C_{X2} + \Delta C_{X3} + \Delta C_{X4} + \Delta C_{X5} + \Delta C_{X6} + \Delta C_{X7} + \Delta C_{X8} + \Delta C_{X9} + \Delta C_{X10} + \Delta C_{X11} + \Delta C_{X12} + \Delta C_{X13}$$

The decoupling effort model is as follows:

$$D_t = -\frac{\Delta F}{\Delta C_{X1}}$$

Decoupling effect of different influencing factors is obtained by model decomposition:

$$D_t = -(\Delta C_{X2} + \Delta C_{X3} + \Delta C_{X4} + \Delta C_{X5} + \Delta C_{X6} + \Delta C_{X7} + \Delta C_{X8} + \Delta C_{X9} + \Delta C_{X10} + \Delta C_{X11} + \Delta C_{X12} + \Delta C_{X13}) / \Delta C_{X1}$$

$$D_t = D_{X2} + D_{X3} + D_{X4} + D_{X5} + D_{X6} + D_{X7} + D_{X8} + D_{X9} + D_{X10} + D_{X11} + D_{X12} + D_{X13}$$

Among them, D_t, D_{X2}, D_{X3}, D_{X4}, D_{X5}, D_{X6}, D_{X7}, D_{X8}, D_{X9}, D_{X10}, D_{X11}, D_{X12} and D_{X13} respectively represents the decoupling effect of total carbon emissions, the decoupling effect of gross industrial product, the decoupling effect of output carbon intensity, the decoupling effect of industrial energy consumption, the decoupling effect of energy consumption carbon intensity, the decoupling effect of industrial investment volume, the decoupling effect of investment carbon emissions, the decoupling effect of population size, the decoupling effect of per capita carbon emissions, the decoupling effect of industrial technological progress, the decoupling effect of carbon intensity of technological progress, and people Decoupling effect of average industrial added value, energy intensity and economic efficiency.

Decoupling effect judgment: when $D_t \geq 1$, represents strong decoupling effect; When $0 < D_t < 1$, represents weak decoupling effect; When $D_t \leq 0$, represents the undecoupled effect.

2.3.2 Quantitative Decoupling

Quantitative decoupling refers to the process in which environmental pollution is incrementally reduced or stabilized in the course of economic growth. At present, EKC curve is more studied. Kuznets curve theory was first mentioned in 1955 by American economist Kuznets(Kuznets S 1955) when studying the relationship between income distribution difference and economic growth. In 1993, Panayotou(Panayotou T 1993) first proposed "environmental Kuznets curve" based on previous studies.

Current research on EKC curve shows that there are not only inverted "U" type, but also linear, positive "U" type and "N" type(Zhou Z Z 2020). According to the type of image, it is mainly divided into three types, which are first order model, second order model and third order model. The expression is as follows:

$$lnCO_2 = b_0 + b_1 ln(GDP/P) + m_1$$

$$lnCO_2 = b_0 + b_1 ln(GDP/P) + b_2 (ln(GDP/P))^2 + m_2$$

$$lnCO_2 = b_0 + b_1 ln(GDP/P) + b_2 (ln(GDP/P))^2 + b_3 (ln(GDP/P))^3 + m_3$$

Where, b_0, b_1, b_2, b_3 is the regression coefficient, and m_1, m_2, m_3 is the random disturbance term.

Carbon emission CO_2 is not only related to industrial output value GDP and population size P, so other influencing factors are added as control variables to obtain the common model of EKC curve, as shown below:

$$lnCO_2 = b_0 + b_1 ln(GDP/P) + b_2 (ln(GDP/P))^2 + b_3 (ln(GDP/P))^3 + \sum_i \alpha_i lnX_i + \mu$$

Where, X_i is the i-th influencing factor and α_i is the regression coefficient of the i-th influencing factor.

3 Empirical Analysis

3.1 Empirical Analysis Framework

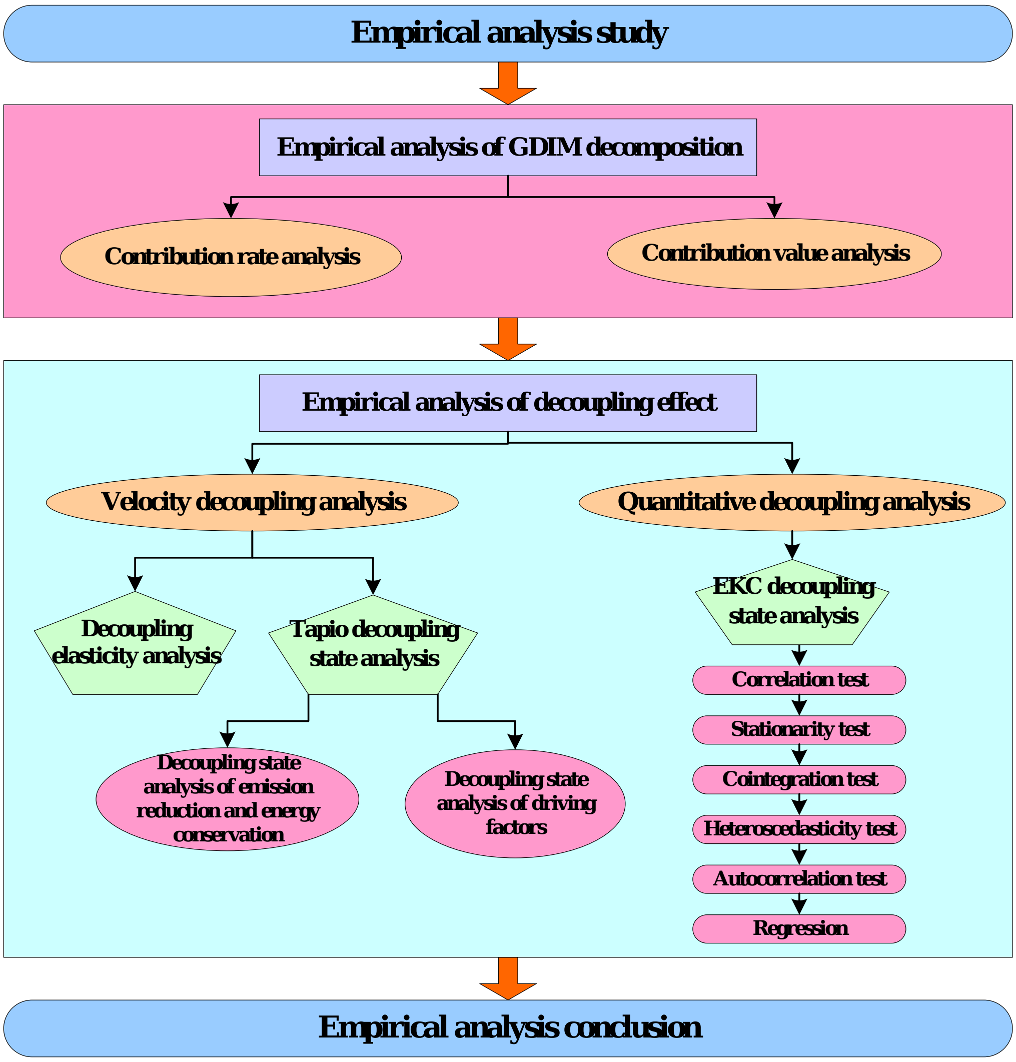


Figure 3 Structural framework of the empirical analysis

3.2 GDIM Factor Decomposition Analysis

3.2.1 Contribution Rate Analysis

Based on GDIM decomposition method, R software version 4.2.2 was used to analyze the factors affecting China's industrial carbon emissions from 2000 to 2019. Output size effect (GDP), output carbon intensity effect (CO_2/GDP), industrial energy consumption effect (E), energy consumption carbon intensity effect (CO_2/E), industrial investment volume effect (I), investment carbon emission effect (CO_2/I), population size effect (P), per capita carbon emission effect (CO_2/P), industrial technology progress effect (T), technological progress carbon intensity effect (CO_2/T) , per capita output effect (GDP/P), energy intensity effect (E/GDP) and economic efficiency effect (I/GDP), as shown in Table 4 and 5.

Table 4 Contribution rates of different factors to carbon emissions

Year	GDP	CO_2/GDP	E	CO_2/E	I	CO_2/I	P
2000-2001	0.017433	-0.005683	0.012943	-0.001475	0.025583	-0.013456	0.001399
2001-2002	0.017795	-0.003101	0.018441	-0.003745	0.033025	-0.017182	0.001304
2002-2003	0.032774	-0.006713	0.033070	0.006159	0.047774	-0.007400	0.001260
2003-2004	0.037459	-0.005289	0.034369	-0.003164	0.045257	-0.013159	0.001206
2004-2005	0.037854	-0.004943	0.030123	0.001487	0.043995	-0.011446	0.001212
2005-2006	0.037233	-0.012447	0.019820	0.002876	0.039838	-0.016109	0.001069
2006-2007	0.042174	-0.023501	0.018220	-0.003220	0.040296	-0.024061	0.001023
2007-2008	0.036000	-0.025538	0.005427	0.002131	0.041441	-0.031996	0.000996
2008-2009	0.013545	-0.003716	0.009996	0.007417	0.049990	-0.028474	0.000993
2009-2010	0.039079	-0.019928	0.014447	0.001694	0.038992	-0.021713	0.000955
2010-2011	0.0378295	-0.013644	0.012825	0.008273	0.018217	0.002827	0.001243
2011-2012	0.015447	-0.003341	0.004815	0.007271	0.035003	-0.021169	0.001500
2012-2013	0.013922	-0.007751	0.004473	0.001612	0.032568	-0.024653	0.001176
2013-2014	0.011333	-0.013935	0.003005	-0.005800	0.025599	-0.026919	0.001313
2014-2015	0.002839	-0.008895	0.000225	-0.006235	0.016640	-0.021760	0.000967
2015-2016	0.009800	-0.012544	0.001653	-0.004698	0.013552	-0.016230	0.001283
2016-2017	0.024200	-0.020601	0.002537	-0.000998	0.012017	-0.010494	0.001096
2017-2018	0.019993	-0.013768	0.005780	-0.00073	0.011582	-0.00650	0.000751

				5		4	
2018-2019	0.008672	-0.003063	0.007266	-0.001735	0.010207	-0.004608	0.000666

Note: Keep six decimal places.

Table 5 Contribution rates of different factors to carbon emissions

Year	CO_2/P	T	CO_2/T	GDP/P	E/GDP	I/GDP
2000-2001	0.010337	0.000903	0.010623	-0.000743	-0.000003	-0.000264
2001-2002	0.013724	-0.000596	0.015272	-0.000901	-0.000002	-0.000721
2002-2003	0.039606	0.003193	0.035830	-0.002849	-0.000001	-0.000767
2003-2004	0.031484	0.003248	0.027857	-0.003619	-0.000002	-0.000333
2004-2005	0.032000	-0.002348	0.033905	-0.003544	-0.000000	-0.000262
2005-2006	0.022854	-0.000252	0.023123	-0.003256	-0.000341	-0.000128
2006-2007	0.015079	0.004257	0.011125	-0.004112	-0.000675	0.000001
2007-2008	0.006916	0.001198	0.006459	-0.002988	-0.001593	-0.000330
2008-2009	0.016871	-0.007048	0.024424	-0.000681	-0.000008	-0.003693
2009-2010	0.016155	0.004621	0.011772	-0.003492	-0.000808	-0.000005
2010-2011	0.020676	0.002903	0.018252	-0.002680	-0.000643	-0.000239
2011-2012	0.010754	-0.002714	0.014749	-0.000614	-0.000311	-0.001239
2012-2013	0.005029	0.000891	0.005234	-0.000531	-0.000258	-0.001142
2013-2014	-0.004090	-0.000378	-0.002313	-0.000327	-0.000204	-0.000704
2014-2015	-0.006978	0.000661	-0.006626	-0.000002	-0.000004	-0.000575
2015-2016	-0.004329	0.000808	-0.003793	-0.000185	-0.000155	-0.000007
2016-2017	0.000494	-0.000254	0.001856	-0.001050	-0.000721	-0.000007
2017-2018	0.004444	0.001240	0.003877	-0.000783	-0.000283	-0.000003
2018-2019	0.004916	0.002854	0.002681	-0.000178	-0.000000	-0.000001

Note: Keep six decimal places.

The period from 2001 to 2019 is divided into four periods, namely 2001-2005, 2006-2010, 2011-2015 and 2016-2019, corresponding to four periods respectively: the Tenth Five-Year Plan period, the Eleventh Five-Year Plan period, the Twelfth Five-Year Plan period and the Thirteenth Five-Year Plan period. Figure 4 includes three figures. The above two figures describe the driving factors with high contribution rate and the driving factors with low contribution rate, so as to more clearly see the contribution rate of each driving factor to carbon emissions. The figure below describes the contribution rate of each driving factor to carbon emissions as a whole and the change trend of carbon emissions.

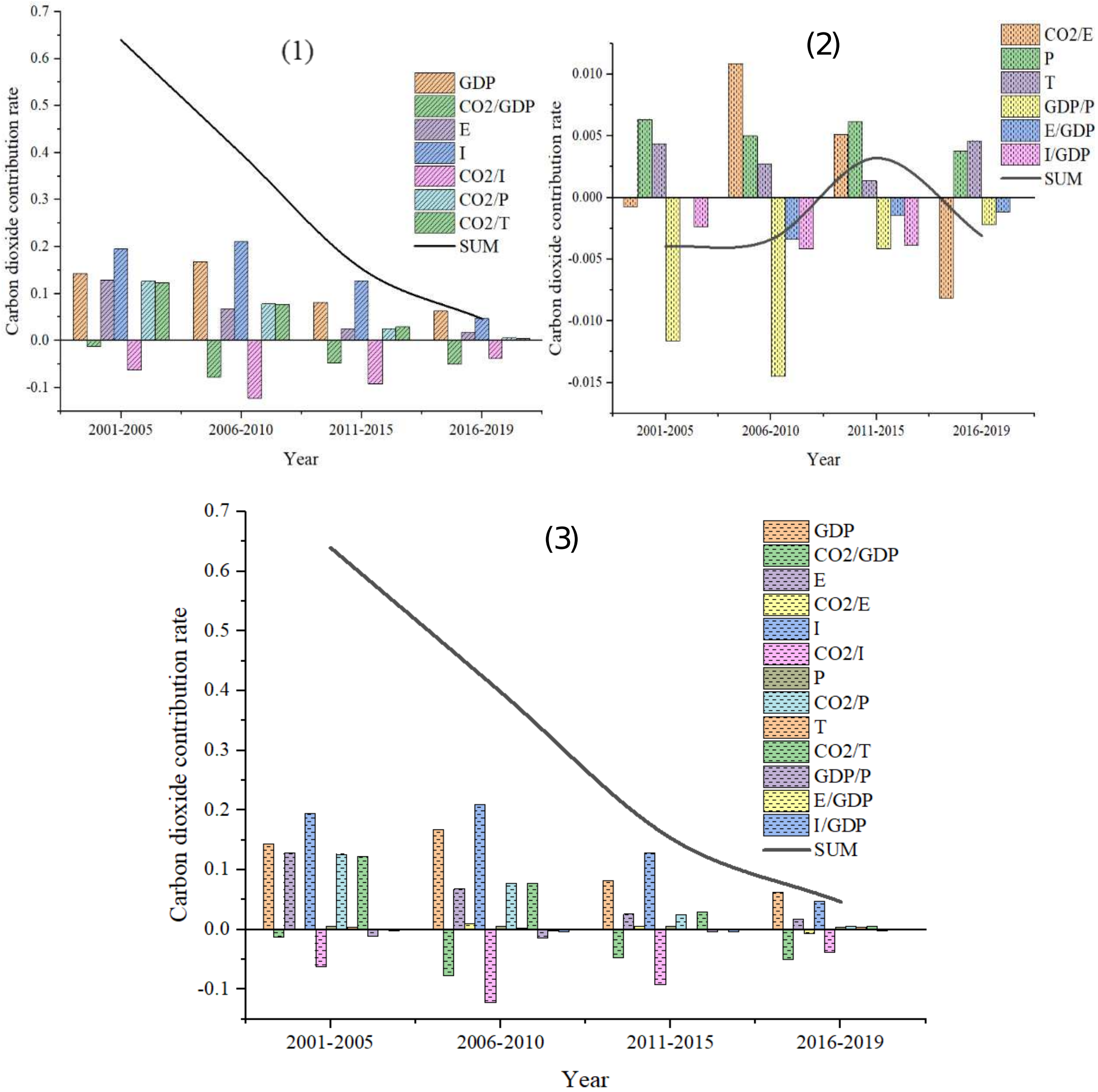


Figure 4 Contribution rate and total contribution rate of different influencing factors to carbon emissions

It can be seen from Table 4, 5 and Figure 4 that: (1) Output scale effect (*GDP*), industrial energy consumption effect (*E*), industrial investment volume effect (I) and population scale effect (P) are the positive driving factors for carbon emissions. (2) Output carbon intensity effect (CO_2/GDP), investment carbon emission effect (CO_2/I), per capita output effect (GDP/P), energy intensity effect (E/GDP), economic efficiency effect (I/GDP) have a negative driving effect on carbon emissions; (3) There are both positive and negative driving effects on carbon emissions: carbon intensity effect of energy consumption (CO_2/E), carbon emission effect of per capita (CO_2/P), industrial technological progress (T), carbon intensity effect of technological progress (CO_2/T); (4) The output scale effect (GDP), industrial energy consumption effect (E), industrial investment volume effect (I), technological progress carbon intensity effect (CO_2/T), investment carbon emission effect (CO_2/I), per capita carbon emission effect (CO_2/P) are the major contribution factors to carbon emissions. (5) From the overall point of view, carbon emissions are declining rapidly, because China has embarked on the ecological path of low-carbon environmental protection, which also shows that the country has achieved significant results in the treatment of carbon emissions.

3.2.2 Contribution Value Analysis

Contribution values of driving factors of China's industrial carbon emissions are decomposed based on GDIM model, and the decomposed driving effects are consistent with the decomposition of contribution rates of driving effects in 3.2.1. The specific contribution values are shown in Table 6, 7 and Figure 5.

Table 6 Contribution values of different influencing factors to carbon emissions

Year	GDP	CO_2/GDP	E	CO_2/E	I	CO_2/I	P
2000-2001	7168.38	-2336.91	5321.95	-606.68	10519.56	-5533.00	575.44
2001-2002	7738.44	-1348.73	8019.29	-1628.65	14361.37	-7471.89	567.25
2002-2003	15297.39	-3133.30	15435.57	2874.69	22298.37	-3453.95	587.89
2003-2004	20899.13	-2950.90	19175.45	-1765.35	25250.18	-7341.91	672.60
2004-2005	24400.13	-3186.50	19416.87	958.25	28358.99	-7377.91	781.48
2005-2006	27792.41	-9290.73	14794.61	2147.09	29737.08	-12024.35	797.74
2006-2007	35077.99	-19546.83	15154.91	-2677.95	33516.34	-20012.95	851.28
2007-2008	32237.13	-22868.72	4859.82	1908.68	37108.70	-28651.32	891.44
2008-2009	12590.9	3454.66	9292.11	6895.26	46470.6	-	922.81

	8				5	26469.74	
2009-2010	39487.57	-20136.38	14597.71	1711.55	39399.52	-21939.45	964.76
2010-2011	41347.53	-14912.69	14018.37	9042.82	19906.79	-3089.94	1358.37
2011-2012	18670.85	-4038.74	5819.55	8788.71	42308.42	-25586.56	1813.19
2012-2013	17840.01	-9932.08	5731.62	2065.50	41732.73	-31590.20	1506.39
2013-2014	14966.12	-18401.41	3968.12	-7659.79	33805.23	-35548.10	1734.57
2014-2015	3698.80	-11589.16	292.97	-8122.61	21679.38	-28349.35	1259.73
2015-2016	12387.83	-15855.98	2089.65	-5937.95	17129.66	-20515.54	1622.15
2016-2017	30132.66	-25651.89	3158.95	-1242.43	14963.27	-13066.42	1364.74
2017-2018	25094.41	-17280.80	7255.01	-923.08	14537.07	-8163.09	942.22
2018-2019	11162.62	-3943.30	9352.52	-2232.78	13138.56	-5931.96	857.50

Note: Keep two decimal places.

Table 7 Contribution values of different influencing factors to carbon emissions

Year	CO_2/P	T	CO_2/T	GDP/P	E/GDP	I/GDP
2000-2001	4250.59	371.12	4368.02	-305.36	-11.94	-108.58
2001-2002	5968.17	-259.22	6641.26	-391.70	-0.80	-313.64
2002-2003	18485.78	1490.37	16723.41	-1329.76	-2.99	-358.14
2003-2004	17565.73	1811.96	15542.33	-2018.88	-11.81	-185.72
2004-2005	20626.61	-1513.76	21854.61	-2284.40	-2.04	-168.61
2005-2006	17059.19	-188.17	17260.02	-2430.60	-254.42	-95.47
2006-2007	12541.81	3540.51	9253.31	-3419.93	-561.50	-4.03
2007-2008	6192.96	1072.43	5783.63	-2675.25	-1426.82	-295.37
2008-2009	15683.51	-6552.14	22704.95	-632.77	-74.49	-3432.89
2009-2010	16323.94	4669.04	11895.26	-3528.82	-816.68	-46.34
2010-2011	22599.20	3173.23	19949.30	-2929.22	-702.93	-261.72
2011-2012	12997.92	-3280.58	17827.23	-741.87	-376.15	-1497.45
2012-2013	6444.00	1142.04	6707.05	-680.10	-330.22	-1463.35
2013-2014	-5400.82	-499.24	-3054.22	-432.10	-269.75	-930.19
2014-2015	-9090.88	861.35	-8632.45	-29.71	-49.23	-749.60

2015-2016	-5472.40	1021.32	-4794.53	-233.72	-195.35	-94.54
2016-2017	614.70	-315.77	2310.75	-1307.89	-898.22	-92.39
2017-2018	5577.51	1556.87	4866.32	-982.62	-355.41	-32.06
2018-2019	6328.12	3673.21	3451.68	-228.80	-0.17	-18.75

Note: Keep two decimal places.

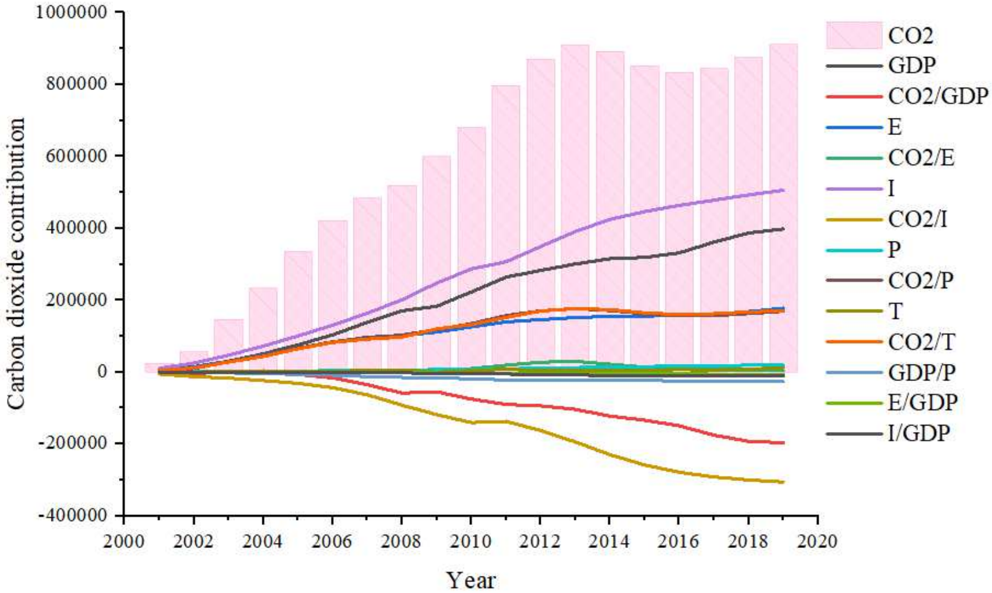


Figure 5 Contribution values of different influencing factors to carbon emissions

It can be seen from Table 6, 7 and Figure 5 that:

(1) The driving factor effects and contribution rates of positive driving effect, negative driving effect, positive and negative driving effect are consistent, which will not be repeated here;

(2) On the whole, carbon emissions first rose, then began to decline, and then began to rise slowly, with the peak in 2013;

(3) Specific analysis of positive driving factors: First: Output scale effect (GDP) contribution value to carbon emissions continued to rise from 2000 to 2005. During this period, China's economy developed rapidly, energy consumption increased, and carbon emissions also increased. During 2005 to 2010, contribution value to carbon emissions first decreased and then increased. From 2011 to 2015, its contribution to carbon emissions continued to decline, and from 2016 to 2019, it showed a stable trend. As China began to save energy and reduce emissions in 2011 and reduce emissions as binding indicators of economic development, carbon emissions began to gradually reduce. Second, industrial energy consumption effect (E) increased from

2000 to 2005, reached a peak of 194,168,700 tons of carbon emissions, decreased in a fluctuating manner from 2006 to 2010, rapidly decreased to 2,929,700 tons from 2011 to 2015, and gradually increased from 2016 to 2019. The changes of output scale effect (GDP) and industrial energy consumption effect (E) are consistent, and there is a linkage between them. It is mainly the increase in output that leads to investment, which in turn increases scale, and also increases energy consumption. Third, population size effect (P) continued to increase from 2000 to 2014, reaching a peak of 17,345,700 tons, and then began to decline. Population size increases productivity, which increases carbon emissions;

(4) Specific analysis of negative driving factors: First, carbon intensity effect (CO_2/GDP) is produced, which plays a very significant role in promoting the decline of carbon emissions, and the overall decline trend is accelerated, reaching a peak of -256,518,900 tons in 2017. Second, investment in carbon emission effect (CO_2/I) accelerated the decline trend of carbon emissions, which reached a peak of 355.4810 million tons in 2014. Third, its output effect per capita (GDP/P) peaked in 2011 at 35,288,200 tons. Fourth, energy intensity effect (E/GDP) promoted the decline trend of carbon emissions quickly, but on the whole, it was a fluctuation decline, reaching a peak of 14.2682 million tons in 2008. Fifth, the effect of economic efficiency (I/GDP) fluctuates on the whole, but the effect of promoting the decline of carbon emissions slows down, reaching a peak of 34.328,900 tons in 2009;

(5) There are both positive and negative driving factors: carbon intensity effect of energy consumption (CO_2/E), per capita carbon emission effect (CO_2/P), industrial technology progress effect (T), carbon intensity effect of technological progress (CO_2/T). The carbon intensity effect of energy consumption (CO_2/E) has a positive driving effect from 2007 to 2013, indicating that the carbon intensity of energy consumption can be reduced only by timely development of the energy structure. The other is the per capita carbon emission effect (CO_2/P), which is basically a positive driving effect on the whole. Since the birth rate of Chinese population has not increased significantly compared to before, but presents a downward trend. The aging degree is very high, and the per capita carbon emission is also high, which presents a positive driving effect on the whole. The effect of technological progress in the third industry (T) also presents a positive driving effect on the

whole. As technological progress does not adjust the energy structure at the same time to bring more output, carbon emissions will increase. The carbon intensity effect of technological progress (CO_2/T) is also positive driving effect in general. Only the adjustment of energy structure can reduce carbon emissions in very few years;

(6) Comparison of contribution values to carbon emissions. Positive driving effect: output size effect (GDP)> industrial energy consumption effect (E)> population size effect (P); negative driving effect: investment carbon emission effect (CO_2/I)> output carbon intensity effect (CO_2/GDP)> output per capita effect (GDP/P)> economic efficiency effect (I/GDP)> energy intensity effect (E/GDP).

3.3 Decoupling Effect Analysis

This section mainly analyzes the decoupling elasticity analysis of industrial carbon emissions and economic growth, the elasticity analysis of industrial carbon emission reduction and energy conservation, and the decoupling effect of industrial carbon emission drivers.

3.3.1 Decoupling Elasticity Analysis

According to the decoupling elasticity formula, the decoupling elasticity of China's industrial carbon emissions and economic growth in each period is calculated, and the decoupling state of China's industrial carbon emissions and economic growth in different periods is divided. Figure 6 Decoupling status ranking is ranked 1, 2, 3 and 4 according to the advantages and disadvantages of decoupling status The decoupling states from good to bad are strong decoupling, weak decoupling, extended decoupling and extended negative decoupling. The difference of scores can directly see the decoupling relationship between China's industrial carbon emissions and economic growth in different periods.

Table 8 Decoupling elasticity of industrial carbon emissions and economic growth in China

Year	DCO_2	$DGDP$	elasticity e	Decoupling condition
2000-2001	0.0576	0.0875	0.7	Weak decoupling
2001-2002	0.0733	0.0895	0.8	Weak decoupling
2002-2003	0.1953	0.1588	1.2	Expansion decoupling
2003-2004	0.1553	0.1848	0.8	Weak decoupling
2004-2005	0.1580	0.1857	0.9	Expansion decoupling
2005-2006	0.1143	0.1848	0.6	Weak decoupling
2006-2007	0.0766	0.2134	0.4	Weak decoupling
2007-2008	0.0381	0.1842	0.2	Weak decoupling
2008-2009	0.0870	0.0681	1.3	Expansion negative decoupling
2009-2010	0.0817	0.1964	0.4	Weak decoupling

2010-2011	0.1058	0.1848	0.6	Weak decoupling
2011-2012	0.0601	0.0775	0.8	Weak decoupling
2012-2013	0.0306	0.0708	0.4	Weak decoupling
2013-2014	-0.0134	0.0585	-0.2	**Strong decoupling**
2014-2015	-0.0298	0.0146	-2.0	**Strong decoupling**
2015-2016	-0.0149	0.0501	-0.3	**Strong decoupling**
2016-2017	0.0080	0.1224	0.1	Weak decoupling
2017-2018	0.0256	0.1003	0.3	Weak decoupling
2018-2019	0.0277	0.0434	0.6	Weak decoupling

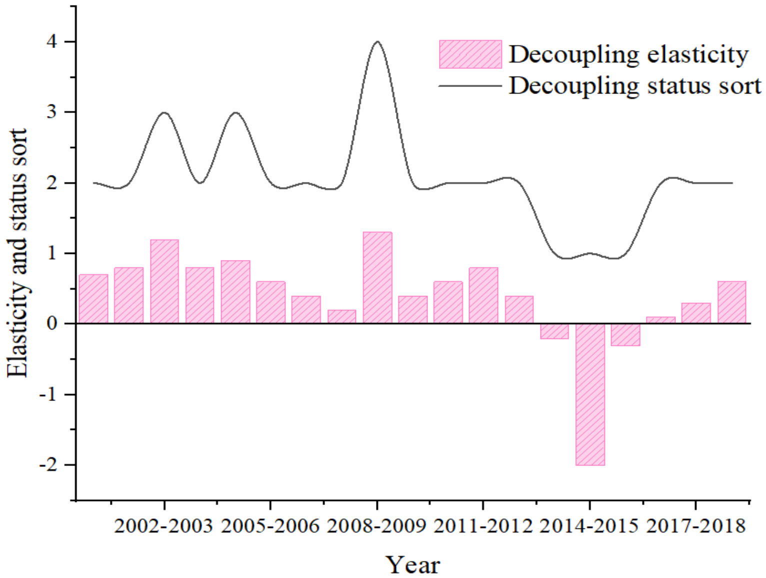


Figure 6 Decoupling elasticity and decoupling status ranking of industrial carbon emissions and economic growth in China

It can be seen from Table 8 and Figure 6 that:

(1) We divide the analysis into four periods. In the first period, from 2000 to 2007, it can be seen that the decoupling of China's industrial carbon emissions and economic growth first worsened and then recovered. In 2003, the decoupling state was the worst year. The economic growth rate is slower than the growth rate of carbon emissions, which is in a relatively unsatisfactory state. Then, the state of decoupling changed from expanding decoupling to weak decoupling, indicating that the decoupling effect of economic growth and China's industrial carbon emissions began to appear. In the second period from 2008 to 2012, the decoupling state was the worst in 2009, with the decoupling elasticity reaching 1.3, indicating a negative decoupling of expansion, and the growth rate of carbon emissions was significantly faster than that of economic growth. This is because after the financial crisis in 2008, the economy was depressed. As a result, the growth rate of industrial carbon emissions was faster than that of economic growth, resulting in the phenomenon of negative expansion decoupling. The third period is 2013-2016, when economic growth and industrial carbon emissions

reach an optimal decoupling state, namely a strong decoupling state. During this period, the country adopted low-carbon policies and regarded low carbon as a binding condition for economic development, so economic growth and carbon emissions reached the optimal decoupling state. The fourth period is 2017-2019, which is in the weak decoupling state. In this stage, the economic growth rate is very slow, while the carbon emission growth rate is very fast.

(2) From the perspective of whole decoupling status sort, the decoupling status of Chinese industrial carbon emission and economic growth is gradually improving, which indicates that Chinese governance policy is effective.

3.3.2 Decoupling State Analysis

(1) Decoupling of Emissions Reduction and Energy Conservation

The analysis of emission reduction elasticity and energy saving elasticity is mainly to clarify the direction of our future efforts to solve carbon emissions.

Table 9 Elasticity of emission reduction and energy conservation of China's industrial carbon emissions

Year	Emission reduction elasticity e_{14}	Decoupling condition	Energy saving elasticity e_3	Decoupling condition
2000-2001	0.884	Expansion decoupling	0.745	Weak decoupling
2001-2002	0.789	Weak decoupling	1.038	Expansion decoupling
2002-2003	1.206	Expansion negative decoupling	1.020	Expansion decoupling
2003-2004	0.900	Expansion decoupling	0.933	Expansion decoupling
2004-2005	1.053	Expansion decoupling	0.808	Expansion decoupling
2005-2006	1.150	Expansion decoupling	0.538	Weak decoupling
2006-2007	0.822	Expansion decoupling	0.436	Weak decoupling
2007-2008	1.379	Expansion negative decoupling	0.150	Weak decoupling
2008-2009	1.757	Expansion negative decoupling	0.727	Weak decoupling
2009-2010	1.118	Expansion decoupling	0.372	Weak decoupling
2010-2011	1.659	Expansion negative decoupling	0.345	Weak decoupling
2011-2012	2.510	Expansion negative decoupling	0.309	Weak decoupling
2012-2013	1.356	Expansion negative decoupling	0.319	Weak decoupling
2013-2014	-0.871	Strong decoupling	0.263	Weak decoupling
2014-2015	-26.061	Strong decoupling	0.078	Weak decoupling
2015-2016	-1.768	Strong decoupling	0.168	Weak decoupling
2016-2017	0.619	Weak decoupling	0.106	Weak decoupling

2017-2018	0.874	Expansion decoupling	0.292	Weak decoupling
2018-2019	0.758	Weak decoupling	0.841	Expansion decoupling

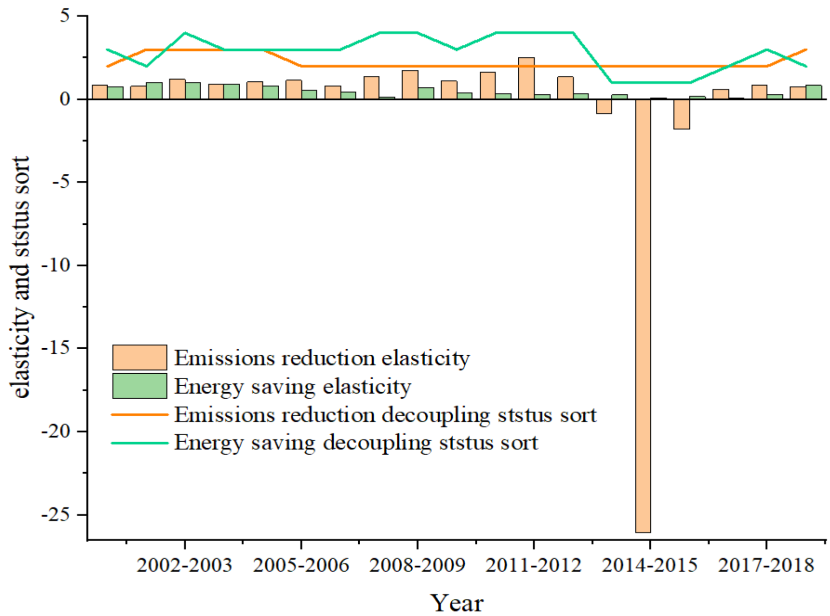


Figure 7 Elasticity of emission reduction, elasticity of energy saving and decoupling status ranking

It can be seen from Table 9 and Figure 7 that:

(1) By comparing the data of energy saving elasticity and emission reduction elasticity, emission reduction elasticity is basically greater than energy saving elasticity, it shows that emission reduction has a lot of effort space, our country should start with emission reduction in the future;

(2) The elasticity of emission reduction fluctuated greatly and experienced four decoupling states. On the whole, the elasticity of emission reduction showed a trend of first increasing and then decreasing. The highest period was from 2008 to 2012. Later, as the country set low-carbon targets, some high-polluting and energy-consuming enterprises were shut down. The elasticity of emission reduction reached its lowest point in 2004. After a few years to maintain a stable trend, in the state of weak decoupling;

(3) The change trend of energy conservation elasticity is small. From 2000 to 2005, when the economy was vigorously developed, energy conservation was only advocated. Later, energy conservation began to be incorporated into the law, making it mandatory;

(4) In terms of decoupling status ranking, the elastic decoupling status of emission reduction and energy conservation showed a trend of improvement on the whole, and relevant national policies played a decisive role.

(2) Decoupling Effect of Different Driving Factors

Through analyzing the decoupling effect of the driving factors of carbon emission, it can be more concrete to understand that we should solve the problem of carbon emission from those driving factors.

Table 10 Decoupling effect of driving factors of industrial carbon emissions in China

Year	D_t	D_{X2} (10^{-5})	D_{X3}	D_{X4} (10^{-6})	D_{X5}	D_{X6} (10^{-5})	D_{X7}
2000-2001	-5.92	6.20	-1.68	7.11	-1.08	20.20	-0.22
2001-2002	-7.17	2.93	-2.29	16.00	-1.41	21.50	-0.19
2002-2003	-10.61	-3.17	-2.26	-13.00	-1.20	4.28	-0.09
2003-2004	-7.48	1.91	-2.07	5.07	-1.07	5.44	-0.07
2004-2005	-7.38	1.47	-1.78	-1.98	-1.07	3.74	-0.06
2005-2006	-5.24	3.10	-1.15	-3.31	-1.02	4.26	-0.04
2006-2007	-2.86	4.03	-0.86	2.74	-0.93	4.29	-0.03
2007-2008	-1.46	3.74	-0.27	-1.73	-1.13	4.88	-0.03
2008-2009	-7.91	-1.07	-1.12	-1.40	-3.64	8.52	-0.06
2009-2010	-2.62	1.92	-0.57	-1.06	-1.18	1.79	-0.02
2010-2011	-3.27	1.07	-0.47	-4.67	-0.56	-0.19	-0.02
2011-2012	-4.13	0.49	-0.38	-8.73	-2.44	2.91	-0.06
2012-2013	-2.26	1.14	-0.37	-2.04	-2.75	3.11	-0.05
2013-2014	1.16	2.23	-0.29	8.40	-2.89	3.41	-0.06
2014-2015	9.57	5.07	-0.08	33.60	-7.96	9.20	-0.17
2015-2016	1.34	1.97	-0.18	7.02	-2.02	1.75	-0.06
2016-2017	-0.28	0.12	-0.11	0.56	-0.74	0.40	-0.02
2017-2018	-0.96	0.77	-0.27	0.45	-0.82	0.26	-0.02
2018-2019	-2.25	0.34	-0.72	2.22	-1.59	0.38	-0.03

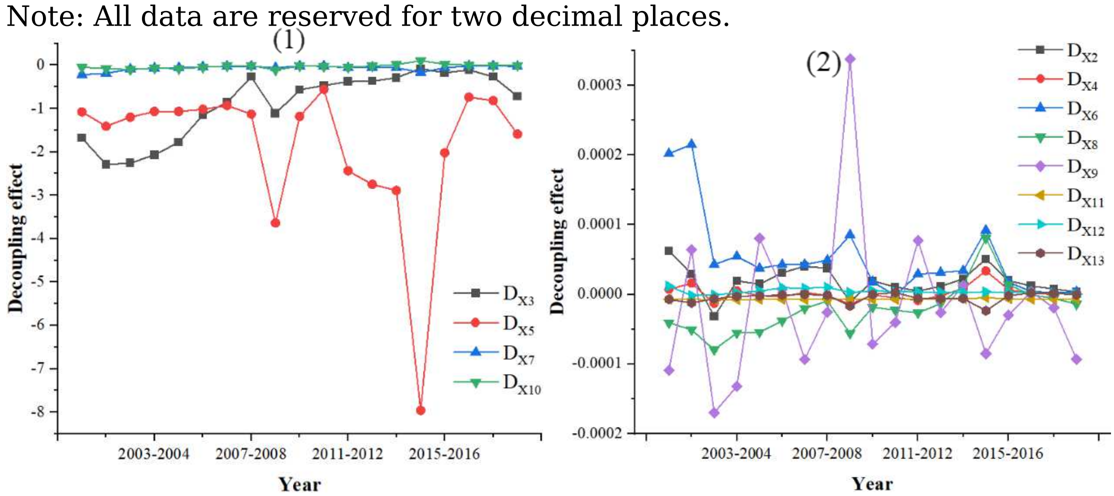
Note: All data are reserved for two decimal places.

Table 11 Decoupling effect of influencing factors on China's industrial carbon emissions

Year	D_{X8} (10^{-5})	D_{X9} (10^{-5})	D_{X10}	D_{X11} (10^{-6})	D_{X12} (10^{-6})	D_{X13} (10^{-6})
2000-2001	-4.08	-10.90	-0.05	-7.21	11.60	-7.13
2001-2002	-5.09	6.41	-0.08	-7.22	-1.55	-12.30
2002-2003	-7.96	-17.00	-0.10	-7.44	-0.72	-6.37
2003-2004	-5.53	-13.20	-0.07	-7.45	1.99	-2.84

2004-2005	-5.44	8.05	-0.08	-7.40	4.79	-2.02
2005-2006	-3.80	70.4	-0.05	-7.39	9.45	-0.10
2006-2007	-2.02	-9.36	-0.02	-7.38	8.81	0.03
2007-2008	-0.96	-2.59	-0.01	-7.32	10.10	-1.28
2008-2009	-5.60	33.80	-0.11	-6.96	2.64	-16.70
2009-2010	-1.84	-7.14	-0.02	-7.28	4.98	-0.23
2010-2011	-2.28	-4.02	-0.03	-7.17	3.93	2.55
2011-2012	-2.66	7.73	-0.05	-6.65	3.46	-5.66
2012-2013	-1.33	-2.60	-0.02	-6.70	3.03	-6.11
2013-2014	1.26	1.27	0.01	-6.43	2.95	-5.89
2014-2015	8.07	-8.51	0.10	-4.79	3.49	-23.50
2015-2016	1.38	-2.98	0.02	-6.24	2.96	-1.95
2016-2017	-5.93	0.36	0.00	-6.82	2.72	2.19
2017-2018	-0.59	-1.91	-0.01	-6.85	1.77	1.57
2018-2019	-1.40	-9.31	-0.01	-6.55	0.36	-0.65

Note: All data are reserved for two decimal places.



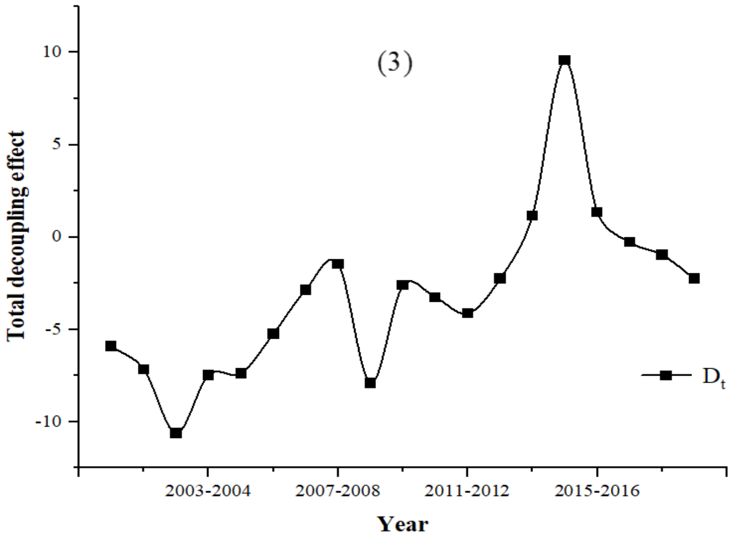


Figure 8 Decoupling effect analysis of driving factors

It can be seen from Table 10, 11 and Figure 8 that:

(1) From the perspective of total decoupling effect D_t, the strong decoupling effect was distributed from 2013 to 2016, showing undecoupling - strong decoupling - undecoupling on the whole. The degree of the two undecoupling is very different, the degree of the first undecoupling is large, and the degree of the second undecoupling is small;

(2) Analysis of undecoupling effect: Decoupling effect of output carbon intensity D_{X3}, decoupling effect of energy consumption carbon intensity D_{X5}, decoupling effect of investment carbon emission D_{X7}, decoupling effect of technological progress carbon intensity D_{X11} on the whole show undecoupling effect;

(3) Weak decoupling effect analysis: gross industrial product decoupling effect D_{X2}, industrial energy consumption decoupling effect D_{X4}, industrial investment decoupling effect D_{X6}, energy intensity decoupling effect D_{X12} on the whole show weak decoupling effect;

(4) Analysis of strong decoupling effect: Only the strong decoupling effect period exists in total decoupling effect, the strong decoupling period indicates that Chinese industrial carbon emissions are reducing at the same time, economic growth is accelerating, the two have very strong decoupling relationship, this is also our very expected to achieve the state.

(5) Analysis of weak decoupling effect and undecoupling effect: Population size decoupling effect D_{X8}, per capita carbon emission decoupling effect D_{X9}, industrial technological progress decoupling effect D_{X10} and economic efficiency decoupling effect D_{X13} showed a weak decoupling effect after 2013.

It is possible that relevant national policies at that time made population size, per capita carbon emission, industrial technological progress, economic efficiency and carbon emission decoupling, but the decoupling effect was relatively small. It also needs to continue to intensify efforts to achieve a strong decoupling of carbon emissions in many sectors.

3.4 Quantitative Decoupling Analysis

According to the three EKC curves constructed in this paper, the test and regression of the three models are carried out, and the appropriate EKC model is selected to analyze the relationship between carbon emission and per capita output, and the form of quadratic function and cubic function form EKC curves are analyzed.

3.4.1 Correlation Test (Screening Variables)

In order to avoid multicollinearity, correlation test was carried out first, and several variables with relatively high correlation were selected as control variables. The selection was made by Pearson correlation analysis.

Table 12 Pearson correlation test

variable	Correlation with CO_2 Pearson and P value	Pearson correlation ranking	variable	Correlation with CO_2 Pearson and P value	Pearson correlation ranking	Weighted ranking
GDP	0.933*** 0.000	9	$lnGDP$	0.975*** 0.000	5	6.2
CO_2/GDP	-0.952*** 0.000	6	$ln(CO_2/GDP)$	-0.879*** 0.000	12	10.2
E	0.993*** 0.000	3	lnE	0.997*** 0.000	3	3
CO_2/E	0.777*** 0.083	13	$ln(CO_2/E)$	0.741*** 0.216	6	8.1
I	0.899*** 0.000	11	lnI	0.971*** 0.000	7	8.2
CO_2/I	0.946*** 0.000	7	$ln(CO_2/I)$	-0.913*** 0.000	10	9.1
P	-0.981*** 0.000	4	lnP	0.927*** 0.000	8	6.8
CO_2/P	0.999*** 0.000	1	$ln(CO_2/P)$	-0.999*** 0.000	2	1.6
T	0.829*** 0.000	12	lnT	0.841*** 0.000	13	12.7
CO_2/T	0.999*** 0.000	1	CO_2/T	1*** 0.000	1	1
GDP/P	0.941*** 0.000	8	$ln(GDP/P)$	0.977*** 0.000	4	5.2
E/GDP	-0.967*** 0.000	5	$ln(E/GDP)$	-0.901*** 0.000	11	9.2
I/GDP	0.918*** 0.000	10	$ln(I/GDP)$	0.925*** 0.000	9	9.3

Note: The weighted ranking is set as 0.3 for the original variable and 0.7 for the variable after logarithm. *** represents a significance level of 1%.

According to the correlation ranking, relatively good variables are CO_2/T,

CO_2/P, E and GDP/P, in which GDP/P is the explanatory variable and the remaining three variables are the control variables. Thus, three environmental Kuznets curve (EKC) models are constructed, namely, the first order model, the second order model and the third order model:

$$CO_2 = b_0 + b_1 ln(GDP/P) + a_1 ln(CO_2/T) + a_2 lnE + a_3 ln(CO_2/P) + e$$

$$CO_2 = b_0 + b_1 ln(GDP/P) + b_2 (ln(GDP/P))^2 + a_1 ln(CO_2/T) + a_2 lnE + a_3 ln(CO_2/P) + e$$

$$CO_2 = b_0 + b_1 ln(GDP/P) + b_2 (ln(GDP/P))^2 + b_3 (ln(GDP/P))^3 + a_1 ln(CO_2/T) + a_2 lnE + a_3 ln(CO_2/P) + e$$

Where, CO_2 refers to carbon emission; GDP/P is per capita industrial output; CO_2/T refers to carbon intensity of technological progress; CO_2/P is per capita carbon emission; E is industrial energy consumption; b_0, b_1, b_2, b_3, a_1, a_2 and a_3 are regression coefficients; e is the random disturbance term.

3.4.2 Stationarity Test

The stationarity test is to determine that there is no random trend or to confirm the trend, otherwise the "pseudo-regression" problem will occur. Therefore, in order to avoid the problem of "pseudo-regression", the stationarity of data should be tested first, which is also the unit root test. This paper uses ADF test to judge the stationarity of variables, and the test results are shown in Table 13.

Table 13 Unit root test

variable	t	p	conclusion
$lnCO_2$	-8.188	0.000	steady
$ln(GDP/P)$	-2.334	0.161	unstable
$(ln(GDP/P))^2$	-0.880	0.795	unstable
$(ln(GDP/P))^3$	0.232	0.974	unstable
$ln(CO_2/T)$	-4.083	0.001***	steady
lnE	-1.034	0.741	unstable
$ln(CO_2/P)$	-2.256	0.1969	unstable
$D lnCO_2$	-1.393	0.586	unstable
$D ln(GDP/P)$	-1.975	0.298	unstable
$D(ln(GDP/P))^2$	-1.455	0.556	unstable
$D(ln(GDP/P))^3$	-1.949	0.309	unstable
$D ln(CO_2/T)$	-1.528	0.519	unstable
$D lnE$	-1.132	0.702	unstable
$D ln(CO_2/P)$	-0.690	0.8205	unstable
$D^2 lnCO_2$	-3.213	0.019	steady
$D^2 ln(GDP/P)$	-4.725	0.000	steady
$D^2(ln(GDP/P))^2$	-3.809	0.003	steady
$D^2(ln(GDP/P))^3$	-3.491	0.008	steady
$D^2 ln(CO_2/T)$	-16.131	0.000***	steady
$D^2 lnE$	-3.492	0.008***	steady

$D^2 ln(CO_2 / P)$	-3.938	0.0104	steady

Note: *** represents a significance level of 1%.

It can be seen from Table 13 that the original sequence $lnCO_2$ and $ln(CO_2 / T)$ are stable, while the original sequence of other variables is not stable. All variables are unstable after first-order difference, followed by second-order difference, all variables are stable.

3.4.3 Cointegration Test

Cointegration test is used to test whether there is a long-term stable co-integration relationship between non-stationary time series. The premise of the cointegration test is that the variables must satisfy the stability of the same order. It can be seen from Table 13 that all variables are second-order stationary, so the co-integration test is conducted on the original sequence of variables to test whether there is a long-term equilibrium relationship between variables.

Table 14 Cointegration test of three EKC models

	Augmented Dickey-Fuller test statistic	
	t-Statistic	p-value
Primary model	-4.3747	0.0032
Quadratic model	-4.4817	0.0026
Cubic model	-4.3678	0.0033

Table 14 shows that the P-value of the three EKC models is all less than 0.05, indicating that the original hypothesis is rejected and the alternative hypothesis is accepted when the confidence level is 95%. The results of the co-integration test show that the null hypothesis of no co-integration relationship is rejected, and the long-term co-integration relationship between the variables of the three models is considered.

3.4.4 Heteroscedasticity Test

Heteroscedasticity means that the random error terms have different variances relative to the observed values of different explanatory variables. The heteroscedastic test is designed to exclude the correlation between the variance of the random error term and the observed value of the explanatory variable. If there is correlation, it is considered that the model has heteroscedasticity. The test methods of heteroscedasticity include BP test, Goliser test and White test. The specific test results are shown in Table 15.

Table 15 Heteroscedasticity test of three EKC models

		Breusch-Pagan-Godfrey	Glejser	White
Primary model	F-statistic	1.9591	2.3732	1.6811
	Prob. F(4,15)	0.1528	0.0988	0.2065
	Obs*R-squared	6.8630	7.7514	6.1905

	Prob. Chi-Square(4)	0.1433	0.1011	0.1854
	Scaled explain SS	4.6892	6.0794	4.2297
	Prob. Chi-Square(4)	0.3207	0.1933	0.3758
Quadratic model	F-statistic	1.4706	1.8573	2.2592
	Prob. F(5,14)	0.2608	0.1661	0.1054
	Obs*R-squared	6.8872	7.9759	8.9310
	Prob. Chi-Square(5)	0.2292	0.1576	0.1118
	Scaled explain SS	3.8937	5.7025	5.0492
	Prob. Chi-Square(5)	0.5648	0.3362	0.4099
Cubic model	F-statistic	1.8853	1.7304	2.1027
	Prob. F(6,13)	0.1590	0.1914	0.1231
	Obs*R-squared	9.3057	8.8804	9.8502
	Prob. Chi-Square(6)	0.1571	0.1804	0.1311
	Scaled explain SS	4.3119	6.2682	4.5642
	Prob. Chi-Square(6)	0.6346	0.3938	0.6008

Table 15 shows that the p-values of the three EKC models are all less than 0.05, indicating that the original hypothesis is accepted and the alternative hypothesis is rejected when the confidence level is 95%. The original hypothesis is that the random error term has homoscedasticity, and the alternative hypothesis is that the random error term has heteroscedasticity. Therefore, the heteroscedasticity test results of the three EKC models show that the random error terms have homoscedasticity, that is, they pass the heteroscedasticity test.

3.4.5 Autocorrelation Test

Autocorrelation refers to the correlation between the expected values of random error terms, which is called autocorrelation or sequence correlation. There are DW(Durbin-Watson) test and LM(Brosch-Godfrey) test to test autocorrelation.

Table 15 Autocorrelation-DW test of three EKC models

model	Durbin-Watson stat
Primary model	2.0704
Quadratic model	2.1165
Cubic model	2.0835

DW(Durbin-Watson) test in Table 16 shows that DW is 2.07, suggesting that there is no first-order autocorrelation. Since DW is limited to testing only first-order autocorrelations, LM tests are being performed.

Table 16 Autocorrelation-LM test of three EKC models

Primary model	F-statistic	0.5989	Prob. F(2,13)	0.5639
	Obs*R-squared	1.6873	Prob.Chi-Square(2)	0.4301

Quadratic model	F-statistic	1.3909	Prob. F(2,12)	0.2862
	Obs*R-squared	3.7638	Prob.Chi-Square(2)	0.1523
Cubic model	F-statistic	2.4424	Prob. F(2,11)	0.1325
	Obs*R-squared	6.1503	Prob.Chi-Square(2)	0.0462

As can be seen from the LM test results in Table 17, if Prob. F values are all greater than 0.05. Therefore, it can be considered that the three EKC models have no autocorrelation at a confidence level of 98% and pass the autocorrelation test.

3.4.6 Regression

The regression analysis of the three EKC models was carried out, and the overall significance of the three EKC models and the significance of different variables were judged by F test and t test. The specific results are shown in Table 17.

Table 17 Regression results of three EKC models

Model	Variable	Coefficient	Std. Error	t-Statistic	Prob.
Primary model	$ln(GDP/P)$	-0.0498	0.0156	-3.1832	0.0062
	$ln(CO_2/T)$	0.3955	0.0986	4.0107	0.0011
	lnE	0.4546	0.0681	6.6749	0.0000
	$ln(CO_2/P)$	0.0508	0.0104	4.8881	0.0002
	C	4.1721	0.1952	21.3782	0.0000
	F-statistic	32525.9563	Prob.	0.0000	
	R-squared	0.9999	Adjusted R-squared	0.9999	
Quadratic model	$ln(GDP/P)$	-0.0541	0.0291	-1.8600	0.0840
	$(ln(GDP/P))^2$	0.0021	0.0117	0.1778	0.8615
	$ln(CO_2/T)$	0.3990	0.1039	3.8413	0.0018
	lnE	0.4599	0.0765	6.0100	3.1994
	$ln(CO_2/P)$	0.0507	0.0108	4.6982	0.0003
	C	4.0751	0.5818	7.0047	0.0000
	F-statistic	24340.8727	Prob.	0.0000	
	R-squared	0.9999	Adjusted R-squared	0.9998	
Cubic model	$ln(GDP/P)$	-0.0110	0.0333	-0.3294	0.7471
	$(ln(GDP/P))^2$	-0.0337	0.0201	-1.6726	0.1183
	$(ln(GDP/P))^3$	0.0337	0.0162	2.0835	0.0575
	$ln(CO_2/T)$	0.3653	0.0947	3.8568	0.0020
	lnE	0.2952	0.1048	2.8173	0.0145
	$ln(CO_2/P)$	0.0627	0.0113	5.5592	0.0001
	C	6.3304	1.2020	5.2664	0.0002
	F-statistic	25125.64	Prob.	0.0000	
	R-squared	0.9999	Adjusted R-squared	0.9999	

It can be seen from Table 17 that all three EKC models pass the F test. So, it indicates that the explanatory variables selected in this paper are suitable for explaining the changes of carbon emissions. However, the T-test of different variables shows that only EKC model 1 has passed the T-test, and all explanatory variables are considered significant, while $ln(GDP/P)$, $(ln(GDP/P))^2$ and $(ln(GDP/P))^3$ in the quadratic model and cubic model of EKC are not significant.

It can be seen from the regression coefficient that the regression coefficients of technological progress carbon intensity CO_2/T, per capita carbon emission CO_2/P and industrial energy consumption E are positive in the three EKC curves, and the sign of GDP/P is stable. The sign of $ln(GDP/P)$ is also stable, but the sign of $(ln(GDP/P))^2$ is unstable. For every 1% increase in carbon intensity of technological progress, industrial carbon emissions will increase by 0.395%. For every 1% increase in per capita carbon emissions, industrial carbon emissions will increase by 0.0508%; For every 1% increase in industrial energy consumption, industrial carbon emissions will increase by 0.4546%. Every 1% increase in per capita industrial output value will reduce industrial carbon emissions by 0.0498%, which also proves the decoupling relationship between economic growth and carbon emissions.

Then R software 4.2.2 was used to draw images of quadratic and cubic functions of this paper's EKC, and the morphology of the three functions was observed, as shown in Figure 8.

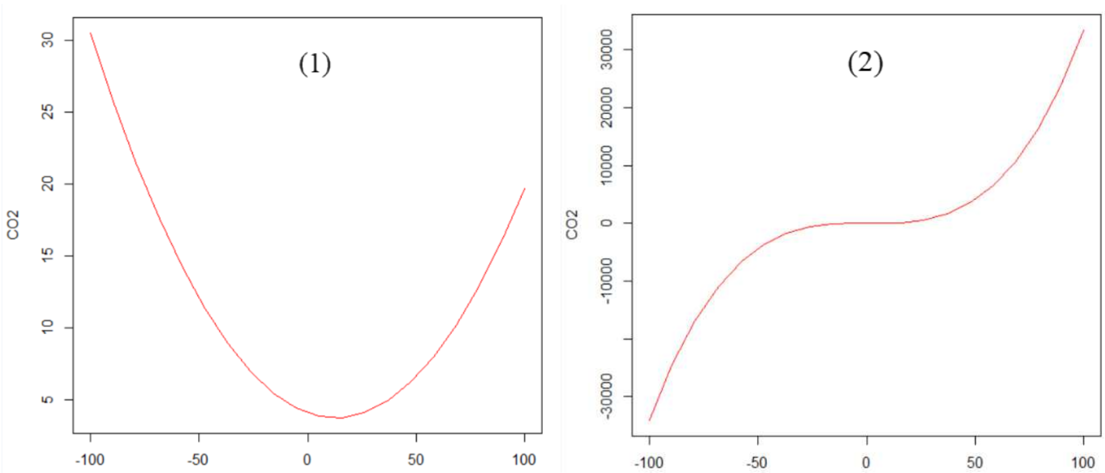


Figure 8 Curve morphology of EKC model in quadratic and cubic function forms

It can be seen from Figure 8 that the form of the quadratic function is “U” and the inflection point is $ln(GDP/P)=11.0987$, which satisfies the EKC hypothesis. The cubic function form is “N” type, indicating that with the increase of per capita production capacity, China's industrial carbon emissions experienced a change process of first rising and then decreasing, and the two inflection points are respectively $ln(GDP/P)=-0.0137$ and $ln(GDP/P)=2.4069$, also satisfying the EKC hypothesis.

4 Prospect

This paper analyzes the driving factors of carbon emission and the impact of different driving factors on the decoupling of carbon emission and economic growth rate. However, in the quantitative decoupling analysis, only individual driving factors are selected instead of all driving factors as independent variables to establish a regression model. Whether the number of driving factors has an impact on the final results needs to be further studied in the future. Second, whether there is a lag effect in economic growth, and whether this year's carbon emissions will have an impact on economic growth next year or even in the following years. Finally, there are many decomposition models, so it is worth studying how to select the most suitable decomposition model for data characteristics, rather than just using the optimal model for analysis.

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Ethical Approval

Not applicable. This paper studies the aspects related to industrial carbon emissions and economic growth, and there is no violation of ethics.

Consent to Participate

Not applicable.

Consent to Publish

The authors agreed to publish it.

Authors Contribution

Chaofeng Shen is responsible for the writing of the article and the construction of the overall thought framework of the article; Haifeng Xu and Jianfei Pang are responsible for the realization of the article code and Jun Zhang is responsible for the article submission.

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Competing Interests

No competing interest

Declaration of internet statement

The research is original. No conflict of interest exists in the submission of this manuscript, and the manuscript is approved by all authors for publication. I would like to declare on behalf of my co-authors that the work described was original research that has not been published previously, and not under consideration for publication elsewhere, in whole or in part. All the authors listed have approved the manuscript that is enclosed.

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