Influencing Factors and Decoupling Analysis of Carbon Emissions in China's Manufacturing Industry

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Abstract

The manufacturing industry directly reflects national productivity, and it is also an industry with serious carbon emissions, which has attracted wide attention. This study decomposes the influential factors on carbon emissions in China's manufacturing industry from 1995 to 2018 into industry value added (IVA), energy consumption (E), fixed asset investment (FAI), carbon productivity (CP), energy structure (EC), energy intensity (EI), investment carbon intensity (ICI) and investment efficiency (IE) by Generalized Divisia Index Model (GDIM). The decoupling analysis is carried out to investigate the decoupling states of the manufacturing industry under the pressure of "low carbon" and "economy." Considering the technological heterogeneity, we study the influential factors and decoupling status of the light industry and the heavy industry. The results show that: (1) Carbon emissions of the manufacturing industry present an upward trend, and the heavy industry is the main contributor. (2) Fixed asset investment (FAI), industry value added (IVA) are the driving forces of carbon emissions. Investment carbon intensity (ICI), carbon productivity (CP), investment efficiency (IE), and energy intensity (EI) have inhibitory effects. The impact of the energy consumption (E) and energy structure (EC) are fluctuating. (3) The decoupling state of the manufacturing industry has improved. Fixed asset investment (FAI), industry value added (IVA) hinder the decoupling; carbon productivity (CP), investment carbon intensity (ICI), investment efficiency (IE), and energy intensity (EI) promote the decoupling.

Keywords: Manufacturing industry; Carbon emissions; Generalized Divisia Index Model (GDIM); Decoupling analysis

1. Introduction

The greenhouse effect caused by carbon emissions seriously threatens the development of human beings. Effectively solving climate and environmental problems become the primary standard for measuring social development quality (Nwaka et al. 2020; Ahmad et al. 2021). Human activities are vital for the production of carbon emissions. Therefore, the initial research is basically from the perspective of socio-economic. Decomposition analysis is an analytical framework for studying the characteristics of greenhouse gas emissions, which increasingly apply in the study of environment and economy (Song et al. 2011; Yue et al. 2013). Generally speaking, greenhouse gas emissions are determined by the technological level, affluence, energy structure, economic structure, population size, etc. The research scopes of decomposition analysis are broad, primarily including

countries, regions, and industries (Chen et al. 2018; Chai et al. 2019; Meng and Zhou 2020).

With the rapid development of industrialization, China achieved the "Made in China," which brought about economic leaps. Meanwhile, China became the largest carbon emitter globally (Choi and Oh 2014; Tan and Lin 2018). Data from the China Statistical Yearbook showed that in 2017 and 2018, the manufacturing industry's industrial added value accounted for 28.11% and 27.84% of the gross domestic product (GDP). Energy consumption accounted for 54.65% and 61.88% of the total energy consumption, respectively. At present, China's economic growth is still dominated by the manufacturing industry (Zhang et al. 2016). Therefore, exploring the driving factors and decoupling status of the manufacturing industry at different times are the basis for verifying the effects of carbon reduction policies.

The low-carbon status depends mainly on the effective utilization of resources rather than on absolute reductions in resource consumption and carbon emissions. In China, the manufacturing industry is the central pillar industry of the economy, which is inevitably accompanied by high carbon emissions. Exploring the relationship between economic development and synchronous carbon emissions change has been the primary national sustainable development issue. The main contributions of this study are as follows: (1) Estimating the carbon emissions of the manufacturing industry, the light industry, and the heavy industry from 1995 to 2018 in China. (2) The GDIM is established to study the absolute and relative influential factors on carbon emissions of the manufacturing industry. Meanwhile, the influential factors of the light industry and the heavy industry are analyzed, respectively. (3) The decoupling model effectively distinguishes the decoupling status and the influential factors on the decoupling effect. This study aims to investigate the driving factors and inhibitory factors of carbon emissions on the manufacturing industry, analyze the manufacturing industry's decoupling states, and explore the path of reducing carbon emissions and achieving sustainable development.

The remaining contents are: Section 2 is the literature review of the development and application of decomposition models and decoupling analysis; Section 3 presents the main models and data sources. Section 4 is the results and discussions. Section 5 puts forward the conclusions and policies.

2. Literature review

2.1 Comparison of the decomposition method

Decomposition methods conduct quantitative research on the contribution of influencing factors to the changes in energy or environment. Currently, the commonly used energy identities are IPAT identity and Kaya identity. Proposed by (Ehrlich and Holdren 1970), the IPAT identity reflected the impact of the environment with population, per capita wealth, and technological level. Kaya identity was proposed by (Kaya. 1989), and it reflected the factors that lead to the change of carbon emissions (Pui and Othman 2019; Ortega-Ruiz et al. 2020).

To verify whether the decomposed variables better reflect the mechanism of influencing factors than the original variables, (Hwang et al. 2020) conducted a multivariate cluster analysis to study the CO_2 generated by fossil fuels with the IPAT/Kaya identity. The results showed that decomposition variables were more helpful in identifying the relevant drivers. Based on the IPAT identity, (Waggoner et al. 2002) further decomposed the technology level T into the technology consumed on per unit of GDP and the environmental impact on per unit of technology, which is called the ImPACT identity. However, (York 2002) believed that both the IPAT and ImPACT models have some limitations, reflecting the effect of independent variables on the linear change of

dependent variables. To make up for the deficiencies of the IPAT model and analyze the influence factors on the nonlinear environmental dependent variables, York further established the STIRPAT method based on IPAT identity. Subsequently, many scholars have conducted extensive research on the STIRPAT model (Xu et al. 2016; Nasrollahi et al. 2020; Ma et al. 2020). The IPAT model, the ImPACT model, and the STIRPAT model have similar conceptual foundations while different purposes. (York et al. 2003) discussed the relationship between the three formulas and improved the STIRPAT model by establishing the concept of ecological elasticity. The results showed that the STIRPAT model with ecological resilience explained the driving force of environmental impacts more accurately. The model not only provided a scientific basis for ecological change but also identified factors that may be most sensitive to policy. Nowadays, the extended model basing on the concept of the IPAT model promoted the decomposition method. Introducing the industrial structure and urbanization level into the IPAT model (Li et al. 2011) adopted the Path-STIRPAT model to study the driving forces of carbon emissions in China. The results believed that the most significant impact on carbon emissions was per capita GDP, followed by industrial structure, population, urbanization, water, and technological level. To further figured out the role of energy in the environment, (Wen and Li 2019) introduced energy into the IPAT model and used the IPAT-E model to explore the influencing factors of regional carbon emissions in China.

The decomposition methods are commonly used in carbon emissions and are roughly divided into two categories: one is Index Decomposition Analysis (IDA), which is a simple index decomposition analysis. And the other is Structural Decomposition Analysis (SDA), Which is a structural decomposition method combined with an input-output model. IDA method mainly includes the Laspeyres index and Divisia index decomposition method. The Divisia index decomposition method mainly includes Arithmetic Mean Divisia Index (AMDI) and Log Mean Divisia Index (LMDI). The LMDI decomposition method is further divided into LMDI decomposition and LMDI I (II) decomposition, which has multiplicative decomposition and additive decomposition simultaneously (Wang and Feng 2018). Table 1 listed the literature on the decomposition method in chronological order.

Table.1 Review of the decomposition model

	Model	Period	Perspectives	Affecting factors
Hatzigeorgiou et al. 2008	AMDI LMDI	1990-2002	Greek	Energy intensity, Fuel share, Population, etc.
Wang et al. 2011	LMDI	1985-2009	Transportation sector	Coefficient, Economic activity, Population, etc
Wang et al. 2012	LMDI	1996-2010	Regions	Energy structural, Economic structure, Energy intensity, Economic output, Population
Gonzalez et al. 2014	LMDI	2001-2008	EU-27 member states	Activity, Structural, Cumulative Intensity
Andreoni and Galmarini 2016	IDA	1995-2007	33 World countries	Energy intensity, Structural changes, Economic growth, etc
Cansino et al. 2016	Enhanced SDA	1995-2009	Sectoral level	Technology, Energy intensity, Structural demand, etc
Su and Ang et al. 2016	SDA	2002	Multi-region	Emission intensity, Leontief structure, Final demand

Muhammad et al. 2016	STIRPAT	1970-2011	Malaysia	Urbanization, Economic, Trade openness, Energy consumption,
Sun et al. 2017	Laspeyres	1997-2002	Power sector	Electricity intensity, GDP, Energy intensity, etc
Dong et al. 2018	SDA	1992-2012	Total economy and sectors	Carbon coefficient, Energy mix, Energy intensity, Input structure
Jia et al. 2019	Extend LMD	1998-2015	The macroeconomic and the microeconomic scales	Industrial structure, Energy intensity and structure, Investment intensity, R&D intensity, and efficiency
Emrah et al. 2019	STIRPAT	2003-2015	19 OECD countries	Urban population, GDP, Share of industry, etc
Jiang et al. 2020	LMDI	2007-2016	Electric power	Population, Economic structure, Industrial structure, Electricity consumption intensity.
Sinha et al. 2020	IPAT	1990-2017	11 Countries	Population, Technological, GDP, Renewable energy consumption

(Alexander Vaninsky 2014) found that the existing decomposition methods were limitations in interdependence and absolute changes of the affecting factors, making factors have mutual dependence in form. Thus, Alexander Vaninsky proposed the Generalized Divisia Index Method (GDIM) and applied the method to study the influencing factors of carbon emissions from 1980 to 2012 in China. The GDIM overcomes the deficiency of the existing decomposition methods and analyses the influencing factors of carbon emissions more comprehensively. At present, the study of the GDIM is still in the initial stage. (Li et al. 2019) applied the GDIM to decompose the affecting factors of the construction industry and predicted the peak of carbon emissions combined with the scenario analysis method in China. Using the GDIM model, (Yang and Shan 2019) studied the driving force of industrial sulfur dioxide emissions in Jiangsu and assessed the contribution rates of carbon emissions factors. It identified the driving factors of regional sulfur dioxide emissions and provided a basis for formulating more reasonable emission reduction policies. (Wang et al. 2018) first adopted the GDIM to analyze the influence factors of carbon emissions on the transportation industry in China. And the improved Tapio model was used to explore the decoupling elasticity of the transportation industry. To identify the drivers of carbon emissions in the mining industry and five sub-sectors in China, (Shao et al. 2016) used the GDIM to decomposition the affecting factors. Meanwhile, the scenario analysis method was established to explore the feasibility of energy mitigation methods and policy suggestions. To avoid the limitation of continuous multiplicative on the LMDI method, (Fang et al. 2020) analyzed the influence of three quantitative factors and five related factors on electricity consumption with the GDIM. At the same time, it revealed the mechanism of electricity consumption.

The reviews of decomposition methods showed that the IPAT and the mIPAT models have a deficiency in analyzing the change of nonlinear influencing factors. The STIRPAT model and LMDI model reflect the influence of nonlinear factors; however, the models cannot distinguish the impact of absolute factors and relative factors. When it comes to industrial carbon emissions decomposition factors, capital increments are more plastic than capital stocks. Meanwhile, fixed asset investment in the incremental sense directly impacts carbon emissions reduction in the manufacturing industry.

Furthermore, the factors related to fixed asset investment can effectively provide a basis for reduction policies (Shao et al. 2017). The GDIM model overcomes the shortcomings of the above decomposition methods, comprehensively distinguishes the contributions of different influencing factors, and can be combined with the decoupling model to explore the relationship between industrial economic development and carbon emissions.

2.2 Literature review on the decoupling model

Decoupling theory is widely utilized to measure the relationship between economic growth, material consumption, and environmental protection. The asynchronous relationship is mainly derived from the response of the government basing on environmental pressure under economic developments. Currently, there are two decoupling models: the OECD decoupling model and the Tapio decoupling model. The OECD decoupling model utilized the ratio of environmental pressure to GDP at the end of the period and the initial period to present the decoupling state, which effectively identifies the correlation between economic development and environmental pollution; however, it cannot distinguish the decoupling status. (Tapio 2005) established the Tapio decoupling model, which overcome the defects of OECD decoupling.

Basing on the LMDI and the Tapio index, (Wang and Yang 2015) quantitatively analyzed the decoupling index of industrial growth and environmental pressure in the Beijing-Tianjin-Hebei region. The results showed that economic growth was the main factor leading to industrial decoupling. Energy structure and energy intensity have an essential impact on the process of industrial decoupling. From the perspective of the industry sector, (Andreoni and Galmarini 2012) and (Lu et al. 2015) utilized a decomposition model to analyze the decoupling relationship of carbon emissions. The distinctions were that (Andreoni and Galmarini 2012) divided the study into two periods and considered factors such as carbon intensity, energy intensity, structural change, and economic activity. The study analyzed the decoupling state of agricultural, thermal production, water, gas, transportation, and service sectors. While (Lu et al. 2015) divided the industry into three main sectors and 38 sub-sectors and studied the decoupling relationship between carbon emissions intensity and economic growth. The most important was that five manufacturing industries had achieved a low-carbon economy in varying degrees. Combining the improved Laspeyres index method with the decoupling model (Diakoulaki and Mandaraka 2007) and (Ren and Hu 2012) studied the decoupling relationship between industry growth and carbon emissions at the national and industry levels. The former took advantage of an improved Laspeyres model to decompose the affecting factors into output, energy intensity, structure, fuel structure, and utility structure. It mainly evaluated the actual efforts and effectiveness of countries in economic development and the environment. The latter divided the factors into industrial scale, energy structure, energy intensity, and public utility structure. And it is believed that the growth of the industry was a significant factor in carbon emissions. To further explore the degree of the economy dependent on energy input, (Bithas and Kalimeris 2013) tried to re-estimate the decoupling effect of energy-economic growth, incorporating the energy/capita GDP ratio into the decoupling model. Results denoted that the energy/capita GDP ratio is closer to the energy attributes than the energy/gross domestic product ratio. (Zhang and Da 2015) decomposed Chinese carbon emissions and carbon intensity into the energy source and the industrial structure by the LMDI method, respectively. Then introduced the decoupling index to analyze the decoupling relationship between carbon emissions and economic growth. From the national perspective, (de Freitas and Kaneko 2011) and (Roinioti and Koroneos 2017) investigated the decoupling state in Brazil and Greece, respectively. The difference was that

the former employed the LMDI decomposition model, while the latter utilized the full decomposition technique developed by JW Sun. Compared with the LMDI model, the complete decomposition technique developed by JW Sun effectively deals with zero values in the data set. Notwithstanding, the decomposition model analyzes the driving factors of carbon emissions; however, it cannot precisely and objectively measure the government's efforts to carbon reduction. Therefore, a decoupling model basing on the GDIM of the manufacturing industry is necessary.

3. Methodology and data

3.1 The Generalized Divisia Index Model (GDIM)

Basing on the principle of Kaya identity, the GDIM decomposes the multi-dimensional factors of carbon emissions and makes up for the shortcoming of the interdependence of factor selection in the existing decomposition methods. At the same time, the absolute and relative factors are investigated to avoid double counting. The expressions of GDIM are as follows:

$$\begin{aligned} &TC = IVA*(TC/IVA) = E*(TC/E) = FAI*(TC/FAI) \\ &E/IVA = (TC/IVA)/(TC/E) \\ &IVA/FAI = (TC/FAI)/(TC/IVA) \end{aligned} \tag{1}$$

Where *TC* stands for carbon emissions; *E* is energy consumption; *IVA* represents the industry value added; *FAI* is fixed asset investment; *EC* represents the energy structure; *CP* denotes carbon productivity; *ICI* is investment carbon intensity; *EI* indicates energy intensity; *IE* means investment efficiency. Furthermore, the formula (1) can be transformed as:

$$\begin{aligned} &TC = IVA*CP \\ &IVA*CP - E*EC = 0 \\ &IVA*CP - FAI*ICI = 0 \\ &IVA - FAI*IE = 0 \\ &E - IVA*EI = 0 \end{aligned} \tag{2}$$

The function $TC(X)$ represents the contribution of factor *X* to carbon emissions. Combined with the above formula, the Jacobian matrix is constructed as:

$$\phi_X = \begin{bmatrix} CP & IVA & -EC & -E & 0 & 0 & 0 & 0 \\ CP & IVA & 0 & 0 & -ICI & -FAI & 0 & 0 \\ 1 & 0 & 0 & 0 & -IE & 0 & -FAI & 0 \\ -EI & 0 & 1 & 0 & 0 & 0 & 0 & -IVA \end{bmatrix} \tag{3}$$

The changes in carbon emissions can be decomposed into the sum of the contributions of affecting factors as:

$$\Delta TC[X \mid \phi] = \int_L \nabla TC^T (I - \phi_X \phi_X^+) dX \tag{4}$$

Where *L* represents the time span; *I* is the identity matrix; "+" means generalized inverse matrix; $\nabla TC = (CP \quad IAV \quad 0 \quad 0 \quad 0 \quad 0 \quad 0 \quad 0)^T$; if the columns of ϕ_X in the Jacobian are linearly independent, then $\phi_X^+ = (\phi_X^T \phi_X)^{-1} \phi_X^T$.

Therefore, the influencing factors on carbon emissions of the manufacturing industry can be decomposed into $\Delta IVA, \Delta E, \Delta FAI$, $\Delta CP, \Delta EC, \Delta ICI, \Delta IE$ and ΔEI. Where $\Delta IVA, \Delta E, \Delta FAI$ are

the absolute influence factors on carbon emissions; ΔCP, ΔEC, ΔICI, ΔIE and ΔEI are the relative influence factors. ΔIVA reflects the effect of output scale; ΔE represents the effect of energy consumption; ΔFAI is the effect of investment scale; ΔCP is the effect of carbon productivity; ΔEC is energy structure effect; ΔICI denotes the impact of investment carbon intensity; ΔEI stands for energy intensity effect; ΔIE is the effect of investment efficiency.

3.2 The decoupling model

The decoupling status classified by the Tapio model is more accurate and not limited by time. According to the elasticity value, the decoupling states can be divided into weak decoupling, strong decoupling, weak negative decoupling, strong negative decoupling, growth negative decoupling, growth connection, recession decoupling, and decline connection. Based on the Tapio model, the decoupling model of carbon emissions in the manufacturing industry is as follow:

$$\begin{aligned}\varphi(TC, IVA) &= \frac{\Delta TC / TC}{\Delta IVA / IVA} \\ &= \frac{IVA}{TC * \Delta IVA} * \quad \Delta TC \\ &= \frac{IVA}{TC * \Delta IVA} * (\Delta IVA + \Delta CP + \Delta E + \Delta EC + \Delta FAI + \Delta ICI + \Delta IE + \Delta EI) \\ &= \frac{\Delta IVA * IVA}{TC * \Delta IVA} + \frac{\Delta CP * IVA}{TC * \Delta IVA} + \frac{\Delta E * IVA}{TC * \Delta IVA} + \frac{\Delta EC * IVA}{TC * \Delta IVA} + \frac{\Delta FAI * IVA}{TC * \Delta IVA} + \frac{\Delta ICI * IVA}{TC * \Delta IVA} + \frac{\Delta IE * IVA}{TC * IVA} + \frac{\Delta EI * IVA}{TC * \Delta IVA} \\ &= \varepsilon_{IVA} + \varepsilon_{CP} + \varepsilon_{E} + \varepsilon_{EC} + \varepsilon_{FAI} + \varepsilon_{ICI} + \varepsilon_{IE} + \varepsilon_{EI}\end{aligned} \tag{5}$$

Where ΔTC and ΔIVA are the change of carbon emissions and the industry value added, respectively; $\varepsilon_{IVA}, \varepsilon_{E}, \varepsilon_{FAI}, \varepsilon_{CP}, \varepsilon_{EC}, \varepsilon_{EI}, \varepsilon_{ICI}, \varepsilon_{IE}$ are the decoupling elastic value of *IVA*, *E*, *FAI*, *CP*, *EC*, *EI*, *ICI,* and *IE*. The decoupling states and elasticity levels are shown in Table 2.

Table.2 Division of decoupling states and elasticity levels

Decoupling states	ΔTC	ΔIVA	φ
Strong negative decoupling	>0	<0	φ<0
Weak negative decoupling	<0	<0	0<φ<0. 8
Expansive negative decoupling	>0	>0	φ>1. 2
Strong decoupling	<0	>0	φ<0
Weak decoupling	>0	>0	0<φ<0. 8
Recessive decoupling	<0	<0	φ>1. 2
Expansive coupling	>0	>0	0. 8<φ<1. 2
Recessive coupling	<0	<0	0. 8<φ<1. 2

3.3 Data source

(1) Classify and code of the manufacturing industry. Due to the inconsistent statistical caliber of industry names from 1995 to 2018, this study mainly refers to the China Statistical Yearbook to unify the data source of industry classification caliber. The classified names and codes for 28 sub-sectors of the manufacturing industry are Processing of Food from Agricultural Products (S1), Manufacture of Foods (S2), Manufacture of Liquor, Beverages and Refined Tea (S3), Manufacture of Tobacco (S4), Manufacture of Textile (S5), Manufacture of Textile, Wearing Apparel and Accessories (S6), Manufacture of Leather, Fur, Feather and Related Products and Footwear(S7), Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products (S8), Manufacture of Furniture(S9), Manufacture of Paper and Paper Products(S10), Printing and Reproduction of Recording Media(S11), Manufacture of Articles for Culture, Education, Arts and

Crafts, Sport and Entertainment Activities (S12), Processing of Petroleum, Coal and Other Fuels (S13), Manufacture of Raw Chemical Materials and Chemical Products (S14), Manufacture of Medicines (S15), Manufacture of Chemical Fibers (S16), Manufacture of Rubber and Plastics Products (S17), Manufacture of Non-metallic Mineral Products (S18), Smelting and Pressing of Ferrous Metals (S19), Smelting and Pressing of Non-Ferrous Metals (S20), Manufacture of Metal Products (S21), Manufacture of General Purpose Machinery (S22), Manufacture of Special Purpose Machinery (S23), Manufacture of Transportation Equipment (S24), Manufacture of Electrical Machinery and Apparatus (S25), Manufacture of Computers, Communication and Other Electronic Equipment (S26), Manufacture of Measuring Instruments and Machinery (S27), Other Manufacture(S28).

(2) The manufacturing industry data in China from 1995 to 2018 are collected from China Statistical Yearbook, China Energy Statistical Yearbook, Statistical Yearbook of the Chinese Investment in Fixed Assets, China Industrial Statistical Yearbook, National Bureau of Statistics, and (Shao et al. 2017). All economic indicators adopted constant prices in 2000. At the same time, we divided the research phase into 1995-2000, 2000-2005, 2005-2010, 2010-2015, 2015-2018, as the stages were mainly in the "Nine Five-Year Plan," "Ten Five-Year Plan," "Eleventh Five-Year Plan," "Twelfth Five-Year Plan" and "Thirteenth Five-Year Plan." Since there is no directly available statistical data on carbon emissions, we estimated the direct carbon emissions of the manufacturing industry from 1995 to 2018 following the calculation method of the Intergovernmental Panel on Climate Change (IPCC). The estimation process is shown in Appendix A.

4. Results and discussions

4.1 The results of carbon emissions

As shown in Figure 1, the total carbon emissions of China's manufacturing industry present an upward trend from 1995 to 2018. From 1995 to 2001, there is a slight downward trend in carbon emissions. However, carbon emissions continue to increase after 2001, with an average annual growth rate of 15.4% from 2001 to 2008. Although carbon emissions fell slightly in 2009, it is still on the rise. It is worth noting that after 2014, carbon emissions show a downward trend. The trend of carbon emissions in heavy industry is roughly the same as that of the entire manufacturing industry. In contrast, the carbon emissions of the light industry change slightly and account for less than 20% of the manufacturing industry. Obviously, the heavy industry is a significant contributor to the carbon emissions of the manufacturing industry, which should be paid more attention to.

After China entered the World Trade Organization in 2001, carbon emissions continue to rise as the market expands and exports increase. Meanwhile, with the expansion of functions in Chinese urban, the demand for infrastructures also goes upward. Notwithstanding that the manufacturing industry's total economic output continues to grow, the carbon emissions problem has gradually emerged. In 2014, the Chinese economy entered a new normal period, which brings an opportunity to develop a green and low-carbon economy. The industrial structure has been adjusted and optimized, and the growth rate of total carbon emissions in the manufacturing industry slow down. Generally, energy consumption is a rigid demand for the development of the manufacturing industry. With the acceleration of industrialization and urbanization, the carbon emissions of the manufacturing industry are severe, especially that of the heavy industry. Therefore, it is necessary to analyze the driving factors of carbon emissions in the manufacturing industry to provide a basis for the reduction strategies. The total carbon emissions of 28 sub-industries of the manufacturing industry are shown in Appendix B.

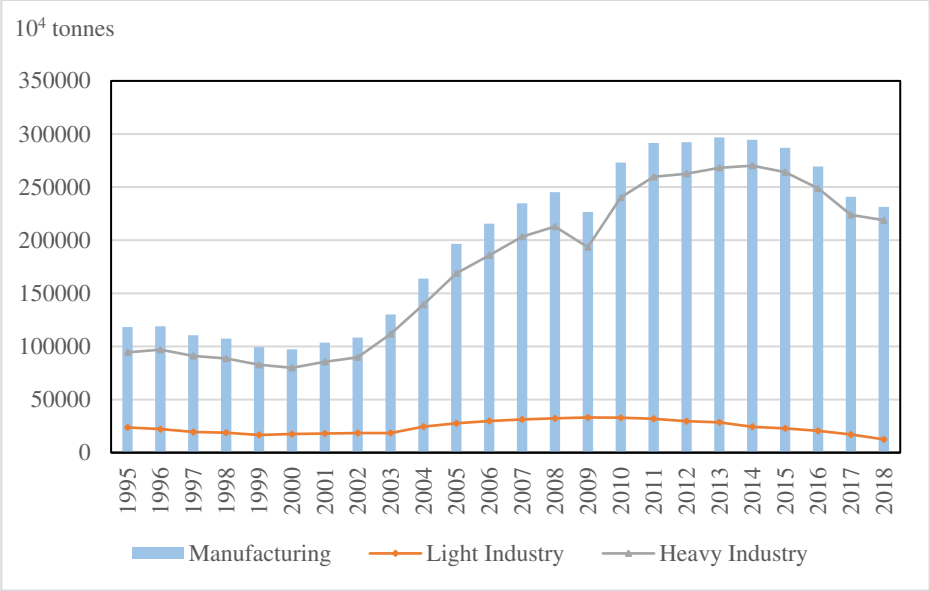

Figure.1 The carbon emissions of the manufacturing industry in China from 1995 to 2018

4.2 The results of GDIM decomposition

4.2.1 Decomposition results of China's manufacturing industry

This study decomposes the carbon emissions of the manufacturing industry in China from 1995 to 2018 based on Eq.(1)- Eq.(4). By taking into account the technological heterogeneity of the light industry and the heavy industry, the influencing factors of carbon emissions are decomposed, respectively. It can be seen from Figure 2 that fixed asset investment (FAI) and industry value added (IVA) are the driving factors. Investment carbon intensity (ICI), carbon productivity(CP), investment efficiency (IE), and energy intensity (EI) are the restraining factors. However, energy consumption (E) and energy structure (EC) present inconsistent effects at different stages.

Among the driving factors, fixed asset investment (FAI) is the most vital factor in increasing manufacturing carbon emissions, and industry value added (IVA) is the main factor. The driving effects of fixed asset investment (FAI) and industry value added (IVA) are not fully manifested during the “Ninth Five-Year Plan” period; however, the driving effects are particularly obvious during the “Twelfth Five-Year Plan” period. Furthermore, during the “Thirteenth Five-Year Plan” period, carbon emissions driven by fixed asset investment (FAI) and industry value added (IVA) is decreased. Since the reform and opening-up, China's economy has been in a stage of extensive growth. The reform of the property rights system and the government management system in the manufacturing sector is still lagging behind. Investment and construction in fixed assets are still at the primary stage, and the output scale needs to be improved. Therefore, during the “Ninth Five-Year Plan” period (1995-2000), the government explicitly proposed transforming the economic growth pattern from extensive to intensive.

During the “Tenth Five-Year Plan” period (2000-2005), China's social productivity and foreign economic relations have experienced significant changes. China entered the World Trade Organization and became the "world factory." Export volume increased sharply. The investment in fixed assets in the manufacturing industry further expanded, leading to increased carbon emissions caused by fixed asset investment (FAI) and industry value added (IVA).

During the “Eleventh Five-Year Plan” period (2005-2010), the continuous improvement of

economic and infrastructure construction increased energy consumption. The global financial crisis in 2008 brought a significant impact on the world economy. To get rid of the crisis as soon as possible, expanding the investment scale to stimulate economic growth is one of the government's main strategies. Increasing investment in fixed assets can solve employment, promote income growth, and maintain social stability. However, it will cause serious environmental issues with too much attention paid to scale expansion and neglect carbon emissions. After the international financial crisis in 2008, the phenomenon of overcapacity in China has also changed from overcapacity in local industries to an overall surplus. Therefore, China first time put forward the constraint target of energy conservation and emission reduction during the “Eleventh Five-Year Plan” period.

During the Twelfth Five-Year Plan (2010-2015) period, China proposed to enhance the core competitiveness of the manufacturing industry. In 2015, China committed in the Paris Agreement: Carbon dioxide emissions will reach a peak around 2030 and strive to reach the peak as soon as possible, and carbon dioxide emissions per unit of GDP will be reduced by 60%-65% compared with 2005. Therefore, at the beginning of the "Thirteenth Five-Year Plan" (2015-2018), the increase in carbon emissions caused by fixed asset investment (FAI) and industry value added (IVA) has been significantly reduced. It showed that China's manufacturing industry had achieved certain results in cleaner production and green transformation under the new economic normal background.

Among the inhibiting factors, investment carbon Intensity (ICI) is the most important reason for reducing carbon emissions, while carbon productivity (CP) is an essential factor. The following are investment efficiency (IE) and energy Intensity (EI). The promotion effect of Investment carbon intensity (ICI) is particularly obvious during the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan" periods, which are 431.123 million tonnes and 666.136 million tonnes, respectively. Investment, consumption, and exports are the "troika" that promotes economic growth, and the Chinese market is mainly in an investment-driven economic growth model. During the"Eleventh Five-Year Plan" period, the government emphasized the resource and environmental pressures on sustainable development caused by blind investment and low-level expansion. Therefore, in the "Twelfth Five-Year Plan," the emphasis is on promoting economic growth to rely on consumption, investment, export coordinated shift. It makes investing in carbon intensity an important reason for reducing carbon emissions. Meanwhile, during the "Eleventh Five-Year Plan" and "Twelfth Five-Year Plan" periods, carbon productivity reduces the carbon emissions from the manufacturing industry by 274.399 million tonnes and 373.394 million tonnes, respectively.

Investment efficiency (IE) and energy intensity (EI) have relatively weak restraint effects on manufacturing carbon emissions. It indicates that the strategy of energy conservation and emission reduction during the “Eleventh Five-Year Plan” period has a particular impact on the manufacturing industry. The results of investment efficiency (IE) shows that fixed asset investment in the manufacturing industry had formed a certain production capacity and achieved a certain level of production technology

The effects of energy consumption (E) and energy structure (EC) are varied in the light industry and the heavy industry. During the "Ten Five-Year Plan" and "Eleventh Five-Year Plan," energy consumption (E) has a promoting effect on the carbon emissions of the manufacturing industry. In contrast, during the "Nine Five-Year Plan," "Twelfth Five-Year Plan," and "Thirteenth Five-Year Plan," energy consumption (E) inhibits carbon emissions. Furthermore, during the "Thirteenth Five-Year Plan" period, the reduction effect of energy consumption (E) is significantly higher than that

of the "Nine Five-Year Plan" and "Twelfth Five-Year Plan" periods. It indicates that the effect of energy consumption has the potential of emission reduction. It is worth noting that during the "Twelfth Five-Year Plan" period, energy consumption (E) has a decreasing impact on the carbon emissions of the light industry while an increasing effect on the heavy industry. The heavy industry is mainly characterized by a certain industrial scale; therefore, the production of the heavy industry is more driven by energy. Thus, the energy consumption of the light industry and the heavy industry is different.

Energy structure (EC) exhibits an inhibitory effect in the "Nine Five-Year Plan" period, and then it shows a promoting effect in the "Ten Five-Year Plan," "Eleventh Five-Year Plan," "Twelfth Five-Year Plan," and "Thirteenth Five-Year Plan." The difference is that in the early period of the "Thirteenth Five-Year Plan," energy structure (EC) has a slight inhibition effect on the light industry carbon emissions. In 2011, several industry policies successively introduced, such as “Development Plan for Industrial Transformation and Upgrading during the Twelfth Five-Year Plan Period,” “Development Plan for the Petroleum and Chemical Industry during the Twelfth Five-Year Plan Period,” and the "Twelfth Five-Year" development plan for sub-sectors such as Pesticides, Rubber, and Paper Chemicals. The policies gradually facilitate the development of a low-carbon economy in the light industry.

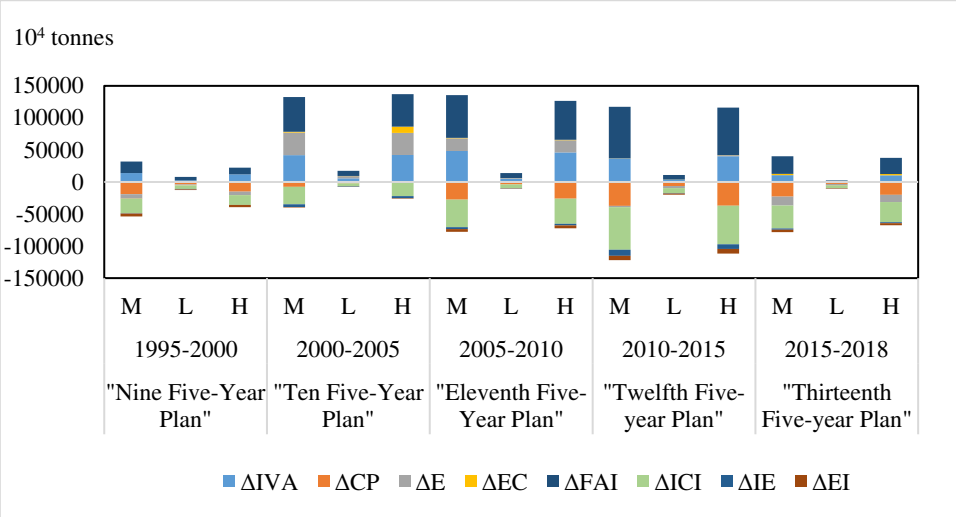

Figure.2 Decomposition results of carbon emissions in China's manufacturing industry from 1995 to 2018

4.2.2 The cumulative contribution on influencing factors of carbon emission in China's manufacturing industry

As shown in Figure 3, the cumulative contribution rate presents a fluctuating trend from 1995 to 2018. The cumulative carbon emissions change from negative to positive after 2002 and show an upward trend until 2014. However, at the beginning of the "Thirteenth Five-Year Plan" period, cumulative carbon emissions begin to decline. The reasons may be that the manufacturing industry developed rapidly due to the comparative advantages of resource endowments and factor costs. Meanwhile, the manufacturing industry gradually formes a pattern of marketization and globalization, which led to a large number of carbon emissions. With the increasing emphasis on the environment, relevant policies, and plans, the growth of carbon emissions in the manufacturing industry slows since 2015.

Fixed asset investment (FAI), industry value added (IVA), and energy consumption (E) are the driving factors of carbon emissions in the manufacturing industry. From 1995 to 2018, fixed asset investment (FAI) is the primary driving force of carbon emissions, which increases the accumulation of carbon emissions to 3359.443 million tonnes and maintains a relatively stable growth trend. Industry value added (IVA), and energy consumption (E) are the essential factors, bringing the cumulative carbon emissions to 1804.789 million tonnes and 377.081 million tonnes, respectively. Energy structure (EC) is the driving factor, and it makes the change range of carbon emissions accumulation small.

Investment carbon intensity (ICI) and carbon productivity (CP) are the main inhibited factors. Meanwhile, energy intensity (EI) and investment efficiency (IE) have a weak inhibition effect. It indicates that the inhibition effect of energy intensity (EI) and investment efficiency (IE) in carbon emissions have not been fully utilized, and the effects need to be further strengthened. China is a developing country; however, the above analysis shows that investment and economic growth are the main reasons for the increase in carbon emissions. Therefore, the mitigation strategies of the manufacturing industry could be formulated from the aspects of improving investment efficiency and carbon productivity. The government should encourage enterprises to eliminate outdated production capacity and optimize energy structure; meanwhile, guide enterprises to pay more attention to the investment and application of energy-saving technologies and equipment. The cumulative contribution of carbon emissions in the light industry and the heavy industry from 1995 to 2018 are shown in Appendix C.

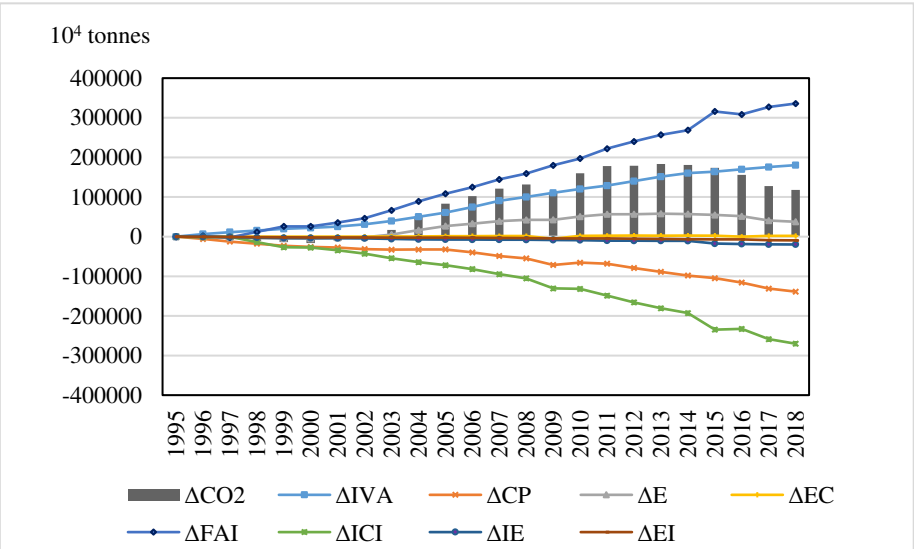

Figure.3 Cumulative contribution of carbon emissions in China's manufacturing industry from 1995 to 2018

4.3 Results of decoupling analysis

4.3.1 Decoupling of carbon emissions in China's manufacturing industry

Table 3 shows the decoupling states of China's manufacturing industry from 1995 to 2018. It demonstrates that due to the distinguishing characteristics of the light industry and heavy industry, the decoupling status of the manufacturing industry is fluctuating.

The manufacturing industry mainly experiences Weak decoupling, Expansive coupling, Expansive negative decoupling, and Strong decoupling. During the Ninth Five-Year Plan period, the manufacturing sector changes from a weak decoupling state to a strong decoupling state. During the "Nine Five-Year Plan" period, the economic system changes from a traditional planned economy

to a socialist market economy. Under the wave of "deindustrialization," China vigorously implemented the reform and opening-up policy. For the first time, it put forward the concept of "expanding domestic demand" and increased investment in infrastructure construction. At the beginning of the "Ten Five-Year Plan," "Eleventh Five-Year Plan," and "Twelfth Five-Year Plan," the manufacturing industry is mainly in the state of expansive coupling. With the rise of e-commerce and online shopping, large-scale manufacturing capacity and industrial clusters formed in coastal areas, making China became the world's largest exporter in 2009.

In the late "Twelfth Five-Year Plan" period, the manufacturing industry begins to show a strong decoupling state and continue to the beginning of the "Thirteenth Five-Year Plan." The outline of the "Twelfth Five-Year Plan" policy points out the main line of development of "traditional manufacturing transfer and upgrade" and puts forward the goal of transforming and upgrading the manufacturing industry. It is not only conducive to improving the production efficiency of the manufacturing industry, improving the relationship between economic development and carbon emissions but also conducive to the green development of the manufacturing industry.

The light industry experiences Strong decoupling, Weak decoupling, Expansive negative decoupling, Expansive coupling, and Strong decoupling. During the "Twelfth Five-Year Plan period, the light industry is mainly in a state of strong decoupling. One of the reasons may be the “Food Industry “Twelfth Five-Year” Development Plan” organized by the National Development and Reform Commission and the Ministry of Industry and Information Technology during 2010-2015. The plan put forward higher energy conservation and emissions reduction than the "Eleventh Five-Year Plan" period. Therefore, the relationship between the industry added value and carbon emissions gradually improves.

The decoupling status of the heavy industry is unsatisfactory, which experiences Weak decoupling, Strong decoupling, Expansive negative decoupling Strong decoupling. The possible reason may be that the heavy industry provides the material foundation for developing the national economy. The government pays more attention to infrastructure construction, which leads to the large carbon emissions of heavy industry. From the "Thirteenth Five-Year Plan," the decoupling status of the heavy industry shows a slight improvement, which presents the strong decoupling in this stage.

Table.3 The decoupling status of the manufacturing industry, the light industry, and the heavy industry

	Periods	Manufacturing Industry	Light Industry	Heavy Industry
"Nine Five-Year Plan"	1995-1996	Weak decoupling	Strong decoupling	Weak decoupling
	1996-1997	Strong decoupling	Strong decoupling	Strong decoupling
	1997-1998	Strong decoupling	Strong decoupling	Strong decoupling
	1998-1999	Strong decoupling	Strong decoupling	Strong decoupling
	1999-2000	Strong decoupling	Expansive coupling	Strong decoupling
"Ten Five-Year Plan"	2000-2001	Expansive coupling	Weak decoupling	Weak decoupling
	2001-2002	Expansive coupling	Weak decoupling	Weak decoupling
	2002-2003	Expansive coupling	Weak decoupling	Weak decoupling
	2003-2004	Expansive coupling	Expansive negative decoupling	Weak decoupling
	2004-2005	Expansive coupling	Expansive negative decoupling	Weak decoupling

"Eleventh Five-Year Plan"	2005-2006	Expansive coupling	Expansive coupling	Weak decoupling
	2006-2007	Expansive coupling	Weak decoupling	Weak decoupling
	2007-2008	Expansive coupling	Expansive coupling	Weak decoupling
	2008-2009	Strong decoupling	Expansive coupling	Strong decoupling
	2009-2010	Expansive negative decoupling	Strong decoupling	Expansive negative decoupling
"Twelfth Five-year Plan"	2010-2011	Expansive coupling	Strong decoupling	Expansive coupling
	2011-2012	Weak decoupling	Strong decoupling	Expansive coupling
	2012-2013	Weak decoupling	Strong decoupling	Weak decoupling
	2013-2014	Strong decoupling	Strong decoupling	Weak decoupling
"Thirteenth Five-year Plan"	2014-2015	Strong decoupling	Strong decoupling	Recessive decoupling
	2015-2016	Strong decoupling	Strong decoupling	Strong decoupling
	2016-2017	Strong decoupling	Strong decoupling	Strong decoupling
	2017-2018	Strong decoupling	Strong decoupling	Strong decoupling

4.3.2 Decoupling contribution of influencing factors

From the decoupling contribution of the influencing factors in Table 4, industry value added (IVA) and fixed asset investment (FAI) hinder the decoupling of manufacturing carbon emissions. From 1995 to 2018, the industry value added decoupling factor always greater than 0. The carbon emissions generated by the industry value added continued to increase, only a small decline in 2010, and then shows an upward trend. It illustrates that with industrialization, economic growth would lead to an increase in carbon emissions. The fixed asset investment decoupling factor is less than zero in 1997, 1999, and 2015, while the fixed asset investment decoupling factor is greater than 0 during the rest of the period. The 1997 Asian financial crisis impacted global finance, causing many large Asian companies to lose money. Bankruptcy, unemployment, social and economic depression, and manufacturing industries are also affected. There is a short-term decline in carbon emissions from fixed asset investment (FAI). After the financial crisis, the carbon emissions generated by fixed asset investment (FAI) fluctuates, the overall trend remained rising.

Carbon productivity(CP), investment carbon intensity (ICI), investment efficiency (IE), and energy intensity (EI) promote the decoupling effect of manufacturing carbon emissions. Carbon productivity (CP) decoupling factor is less than 0 from 2003 to 2005. The rest of the time, it shows as a promotion effect. Carbon productivity has a reciprocal relationship with “carbon emission intensity per unit of GDP,” emphasizing emission output efficiency. Judging whether an industry is low-carbon is mainly to see whether it can effectively use resources, rather than just focusing on the absolute reduction in resource consumption and greenhouse gas emissions. Therefore, carbon productivity should be improved.

The decoupling value of investment carbon intensity (ICI), investment efficiency (IE) continue to be less than zero from 1995 to 2018, which shows that Investment carbon intensity (ICI) and investment efficiency (IE) is beneficial to suppress the increase in carbon emissions from the manufacturing industry. Therefore, it is necessary to reasonably improve the investment carbon intensity, energy intensity, and investment efficiency in energy saving and emission reduction. The effect of energy consumption (E) and energy structure (EC) fluctuates, sometimes promoting carbon emissions and sometimes suppressing decoupling. The development of the manufacturing industry is based on high energy consumption and is inevitably accompanied by high carbon emissions. In the short term, fossil fuels are the primary source of energy. Therefore, with the adjustment of

national economic policies, the improvement of the energy structure still requires long-term plans. The decoupling contribution of the influencing factors in the light industry and the heavy industry are shown in Appendix D.

Table.4 The decoupling contribution of the influencing factors in the manufacturing industry

	Periods	εIVA	εCP	εE	εEC	εFAI	εICI	εIE	εEI	ε
"Nine Five-Year Plan"	1995-1996	0.1237	-0.1067	0.0068	-0.0019	0.0314	-0.0276	-0.0040	-0.0063	0.0156
	1996-1997	0.1440	-0.1991	-0.0854	0.0035	-0.1126	0.0362	-0.0274	-0.0134	-0.2542
	1997-1998	0.1741	-0.2236	-0.0430	0.0003	0.5864	-0.5552	-0.0490	-0.0208	-0.1307
	1998-1999	0.2009	-0.2581	-0.0496	0.0004	0.6769	-0.6409	-0.0566	-0.0240	-0.1509
	1999-2000	0.2329	-0.2871	-0.0581	-0.0115	-0.0031	-0.0682	-0.0063	-0.0098	-0.2113
"Ten Five-Year Plan"	2000-2001	0.2548	-0.1055	0.1483	0.0064	0.7177	-0.5119	-0.0369	-0.0045	0.4685
	2001-2002	0.2655	-0.1931	0.0714	0.0010	0.5199	-0.4107	-0.0190	-0.0135	0.2215
	2002-2003	0.2973	-0.0493	0.2455	0.0112	0.7066	-0.3989	-0.0449	-0.0026	0.7648
	2003-2004	0.3076	0.0091	0.3192	0.0063	0.6441	-0.2873	-0.0292	0.0001	0.9698
	2004-2005	0.3057	0.0043	0.2986	0.0164	0.5576	-0.2221	-0.0147	-0.0002	0.9456
"Eleventh Five-Year Plan"	2005-2006	0.3049	-0.1608	0.1338	0.0021	0.3631	-0.2167	-0.0019	-0.0094	0.4151
	2006-2007	0.3399	-0.1955	0.1307	0.0043	0.4223	-0.2727	-0.0032	-0.0132	0.4127
	2007-2008	0.3844	-0.2429	0.1348	0.0026	0.5896	-0.4304	-0.0079	-0.0112	0.4190
	2008-2009	0.4149	-0.6587	0.0092	-0.2691	0.8220	-0.9925	-0.0295	-0.0316	-0.7354
	2009-2010	0.5128	0.3168	0.4419	0.3903	0.9177	-0.0685	-0.0164	-0.0013	2.4934
"Twelfth Five-year Plan"	2010-2011	0.4780	-0.1504	0.3203	0.0170	1.3693	-0.9434	-0.0659	-0.0055	1.0195
	2011-2012	0.4916	-0.4729	-0.0038	0.0152	0.7957	-0.7478	-0.0142	-0.0317	0.0320
	2012-2013	0.5500	-0.4697	0.0715	-0.0008	0.8212	-0.7190	-0.0104	-0.0260	0.2167
	2013-2014	0.6070	-0.6416	-0.0597	0.0107	0.7988	-0.8275	-0.0051	-0.0345	-0.1519
"Thirteenth Five-year Plan"	2014-2015	0.6686	-1.2318	-0.4195	-0.0496	8.7362	-7.7511	-1.2752	-0.0772	-1.3995
	2015-2016	0.7127	-1.2869	-0.3721	-0.3041	-0.8607	0.2231	-0.1142	-0.0307	-2.0330
	2016-2017	0.8087	-2.1454	-1.5717	0.3004	2.6731	-3.7068	-0.1658	-0.2711	-4.0786
	2017-2018	0.9660	-1.5792	-0.5961	-0.0266	1.7597	-2.3169	-0.0290	-0.0870	-1.9091

5. Conclusions and policy implications

This study first estimates the manufacturing industry's carbon emissions from 1995 to 2018 in China. It indicates that China's manufacturing industry has the potential to reduce carbon emissions, especially the heavy industry. Moreover, the influencing factors on carbon emissions of the manufacturing industry, light industry, and heavy industry are elaborated in detail. Finally, we emphatically study the decoupling states and sources of the discrepancy.

Based on the above analysis, the main conclusions are as follows: First, manufacturing industry carbon emissions show a fluctuating upward trend from 1995 to 2018. Heavy industry is the primary source for promoting carbon emissions in the manufacturing industry. Second, fixed asset investment (FAI) and industry value added (IVA) are the main reasons for promoting carbon emissions. Investment carbon intensity (ICI), carbon productivity(CP), investment efficiency (IE), and energy intensity (EI) are essential factors in reducing carbon emissions. Energy consumption (E) and energy structure (EC) has different effects at different stages. Third, from 1995 to 2018, the light industry's decoupling state is relatively sound, while that of the heavy industry is partially

improved during the "Thirteenth Five-Year Plan." Simultaneously, emphasis should be placed on fixed asset investment (FAI) in hindering the decoupling of the manufacturing industry. And further strengthen the contribution of carbon productivity (CP), investment carbon intensity (ICI), energy intensity (EI), and investment efficiency (IE) on decoupling.

The policy inspirations on energy conservation and emission reduction in China's manufacturing industry mainly including:

(1) The model of economic growth in China is in urgent need of transformation. Relying on investment to stimulate economic development has the hidden danger of overcapacity, which reduces investment returns and the national economy. Furthermore, it will lead to an increase in energy supply, carbon emissions, and environmental pressure. Fixed asset investment(FAI) and industry value added (IVA) has a more obvious linkage effect. Therefore, to overcome the disadvantages of the investment-led growth model and improve the quality of investment, the government should avoid low-benefit production and blind investment. Meanwhile, the economic growth model driven by investment should gradually shift to the consumption-driven economic development model to achieve sustainable development.

(2) By paying full attention to the inhibitory effects of investment carbon intensity (ICI), carbon productivity (CP), investment efficiency (IE), and energy intensity (EI) on manufacturing carbon emissions. At present, energy structure (EC), investment efficiency (IE), and energy intensity (EI) have not fully exerted inhibitory effects on carbon emissions. Notably, energy structure (EC) has the most unsatisfactory emission reduction effect. However, China cannot eliminate the production mode dominated by fossil energy in the short term. Therefore, the energy market's development and improvement should be promoted and establish a reasonable market mechanism of "energy use right" to avoid the "rebound" effect effectively. In the long run, optimizing the energy structure is effective means to reduce the carbon emissions of the manufacturing industry.

(3) Correctly understand the "quantity" and "quality" issues in economic development, focusing on the quality of growth, resource utilization efficiency, and environmental protection. Simultaneously, appropriate subsidies should be adopted to encourage high carbon emissions industries to utilize advanced equipment and improve energy utilization efficiency to achieve sound and rapid economic development of the manufacturing industry.

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Not applicable.

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All the tables and figures are made by the authors. The data took from China Statistical Yearbook, China Energy Statistical Yearbook, Statistical Yearbook of the Chinese Investment in Fixed Assets, China Industrial Statistical Yearbook, National Bureau of Statistics, and (Shao et al. 2017). The data in this paper can be obtained from the authors.

Competing interests:

The authors declare that they have no competing interests.

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Authors' contributions

Baoling Jin: Data curation; Investigation; Methodology; Writing-original draft

Ying Han: Formal analysis; Project administration; Supervision

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Figures

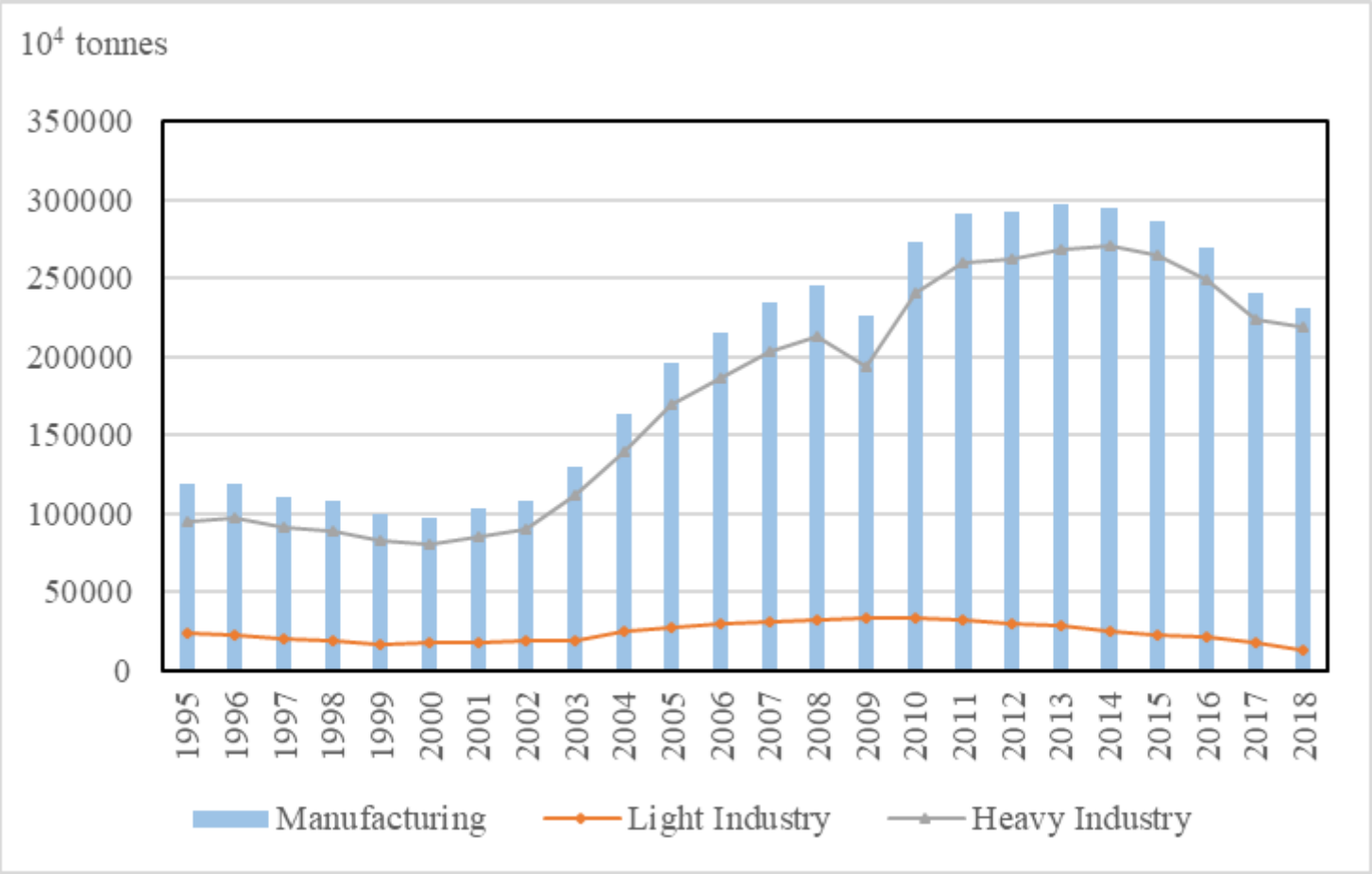

Figure 1

The carbon emissions of the manufacturing industry in China from 1995 to 2018

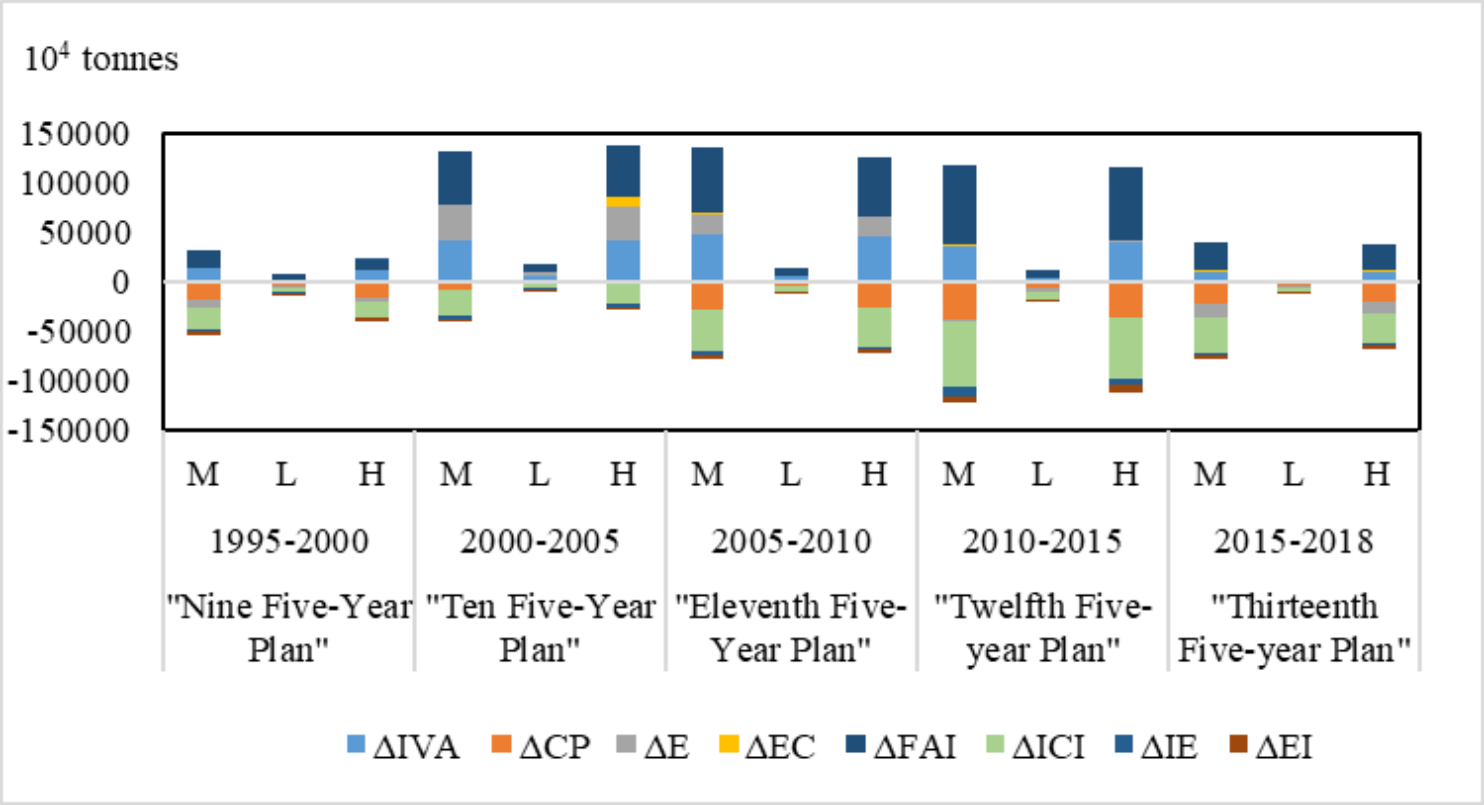

Figure 2

Decomposition results of carbon emissions in China's manufacturing industry from 1995 to 2018

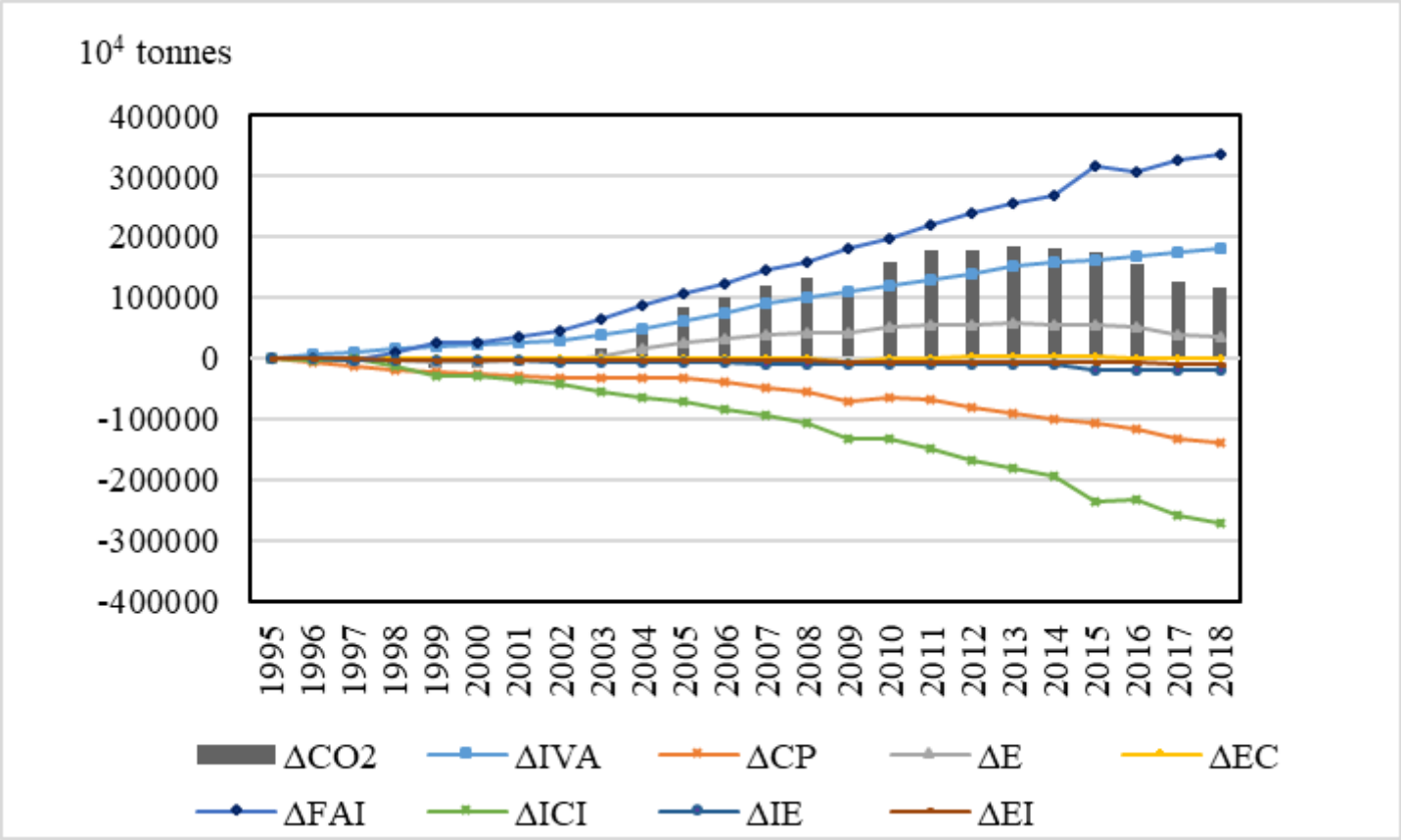

Figure 3

Cumulative contribution of carbon emissions in China's manufacturing industry from 1995 to 2018

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