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Decoupling analysis and peak projection of manufacturing CO_2 emissions from the perspective of investment

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Abstract

Reducing carbon emissions has become an urgent task in China. As the category with the largest economic and emissions contribution to the industry, the carbon emissions research of the manufacturing industry is particularly important. This paper uses the LMDI method to decompose manufacturing carbon emissions into seven influencing factors (i.e., population, urbanization, economic development, investment share, energy intensity, energy structure and emission intensity), in order to explore the factors driving manufacturing carbon emissions during 2003–2018. Then, the paper analyzes the decoupling relationship between manufacturing investment and carbon emissions in 30 provinces. Finally, three scenarios are developed to project future manufacturing emissions at the provincial level up to 2035, and whether manufacturing emissions in 30 provinces can realize peak is discussed. The paper results in three main findings. First, we find that energy intensity played the most important role in decreasing the manufacturing emissions during the whole study period, while the economic development and investment share were the main effect promoting manufacturing carbon emissions. Second, China experienced a process from weak decoupling to strong decoupling between manufacturing invest and emissions. Third, China's manufacturing carbon emissions can only achieve the carbon peaking target in 2030 under the High scenario, and 7 provinces cannot reach the peak before 2035 under the three scenarios.

1 Introduction

Due to the rapid economic development, China's carbon emissions grew six times faster than the rest of the world over the past 20 years, and China accounted for nearly two-thirds of the global increase in CO_2 emissions. By the time of COVID-19 epidemic, China's per capita CO_2 emissions were higher than European Union's (IEA, 2020). In this context, China proposed to realize carbon peak by 2030 and carbon neutrality by 2060 in the

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14th Five-Year Plan. However, the total consumption of fossil energy sources in China still maintains a steady and rapid growth; the carbon emissions reduction still faces huge challenges.

As a pillar industry of China's economy, industrial industry consumed 70% of domestic energy and contributed more than 50% of domestic carbon emissions (Fu et al., 2021), and manufacturing had the greatest economic contribution to industry (NBSC, 2003–2018). Moreover, most of the manufacturing sectors in China produce excessive emissions which accounted for 42–44% of the country's total carbon emissions every year from 1992 to 2012 (Yang et al., 2020a), and there is an energy rebound effect in manufacturing industry, which confirms that China's manufacturing industry has considerable space for emission reduction (Ma et al., 2019a). Policies such as promoting industrial structure can greatly improve the energy efficiency to further reduce the emissions (Liu, 2022), while Chinese government is strengthening its manufacturing industry based on sustainable environmental policies, reforming laws, and regulations governing the manufacturing industry (Beraud et al., 2022). As a result, the manufacturing carbon emissions in China started to decline now (CEADs), so manufacturing carbon emissions reduction is essential for effective environmental policies.

However, with the steady growth of China's manufacturing investment, various industries are still expanding the scale of production, which makes emissions reduction more arduous. Although previous research has covered many economic factors in China, such as added value and economic structure, few studies have systematically studied the investment effect. Large investments were the second most important factor in the increase in CO_2 emissions from Chinese manufacturing companies, with even a greater impact on companies in some cases (Beraud et al., 2022). The increase in manufacturing carbon emissions led by manufacturing investment intensity accounted for one-fifth of the total added value during the Tenth Five-Year Plan (Liu et al., 2019). It is also found that China's domestic investment-driven carbon emissions were equal to about one-third of the total annual carbon emissions in 2007, while the manufacturing sector possessed the second highest share of investment-driven energy consumption and carbon emissions (Fu et al., 2014). On the one hand, investment will promote the industrial development and economic growth of the manufacturing industry, driving the increase in carbon emissions. On the other hand, if the investment is concentrated in low-carbon transformation, it will help reduce the carbon emissions of the manufacturing industry. The investment space for green transformation of manufacturing industry is huge. Under the goal of carbon peak, manufacturing needs investment to develop low-carbon transformation such as energy-saving equipment, clean production technology and resource recycling project. Compared with other unilateral factors such as digitalization and mechanisms such as production and transportation, investment is the key to carbon peaks. Given this, it is necessary to clarify the factors that affect the carbon emissions of China's manufacturing industry and make a comprehensive analysis of the driving factors of the carbon emissions of China's manufacturing industry.

Here, we contribute to previous literature based on the following aspects: firstly, previous studies had unilateral research on the drivers of manufacturing carbon emissions, mainly focusing on economic factor and energy intensity factor; we use the LMDI method to analyze the influential factors of manufacturing sector in China and its 30 provinces in four time periods during 2003–2018 and focus on the investment factor effect. We compare the contribution rates of different factors in different time periods, so that policymakers can better understand the role of these factors to control carbon emissions in a directional way. Moreover, previous literature highlighted the decoupling relationship between economy and carbon emissions, few paid attentions to the investment. Our study is one of the

first to analyze the decoupling index and status between investment scale and manufacturing emissions at the national and provincial levels. Finally, we explore the national and 30 provinces' manufacturing carbon emissions reduction potential by 2035 and identify the peak time through scenario analysis. This is one of the few studies that analyzes the future trajectory of manufacturing carbon emissions by taking provincial differences into account, which can provide useful insights for policymakers to further reduce manufacturing carbon emissions by province.

The rest of the paper is organized as follows: First, we review related previous literatures in Sect. 2. Then, we introduce the methods in Sect. 3. In Sect. 4, we show the results. Finally, conclusions and discussions are presented in Sect. 5.

2 Literature review

Because China is now the world's largest carbon emitter and has set a carbon peak target in 2030, there are numerous studies on the influential factors of carbon emissions in China (see Table S1). The two widely used methods are the LMDI method and the decoupling method. The LMDI model can decompose carbon emissions into multiple distinct effects with no unexplained residuals. It has a wider range of applications and is more adaptable to time-series analysis. Ma et al. (2019b) and Yang et al. (2020b) concluded that per capita GDP and energy efficiency were the main influencing factors that promoted China's carbon emissions by Kaya identity and LMDI method. There are also many studies on carbon emissions conducted by regions or provinces (Zheng et al., 2019; Li et al., 2020; Zhang et al., 2021; Huang & Liang, 2021; Song et al., 2022; Pan et al., 2022; Liu et al., 2021). Dong et al. (2018) and Yang et al. (2020c) found that the energy-intensive industrial structure was one of the main reasons for the change of China's carbon emissions. Thus, many scholars (Fatima et al., 2019; Wen & Li, 2020; Quan et al., 2020; Huang & Matsumoto, 2021) analyzed the drivers of industrial CO_2 emissions in China. The manufacturing industry also became a representative of the industry for carbon emissions research (Liu et al., 2019). Shi et al. (2019) and Fu et al. (2021) explored carbon emissions in China's manufacturing industry and concluded that the industrial activity effect and energy intensity effect were main influencing factors. In general, these existing studies mainly focus on the impact of economic and energy factors; however, few explored from the perspective of investment.

Moreover, there are also many existing studies about decoupling analysis on China's carbon emissions (see Table S2). A few studies focused on decoupling relationship between carbon emissions and economic growth in China (Jiang et al., 2018; Xu et al., 2021; Wu et al., 2019; Liang et al., 2019b; Wu et al., 2018; Pan et al., 2019). Because some scholars (Xu et al., 2017; Liang et al., 2019a; Jia et al., 2021; Chen et al., 2022) found that the impact of industry on the decoupling status of economic growth and carbon emissions was a decisive factor and Wang et al. (2019) concluded only manufacturing sector presented the same trend with the entire industrial sector, manufacturing became the representative of the industrial study. Hang et al. (2019) and Huang et al. (2021) explored the decoupling status of China's manufacturing industry's economic development and carbon emissions. However, most studies ignored the decoupling relationship between investment and carbon emissions although China's investment in manufacturing industry increased fast and was the driving force of carbon emissions (Jin & Han, 2021).

Scenario analysis can be used to predict the future possible development trend of the variables and evaluate policies (see Table S3). Several publications have explored

the future carbon emissions of China's industrial sub-sectors (Lin & Long, 2014; Wen & Li., 2014; Xie et al., 2016; Li et al., 2018; Eheliyagoda et al., 2022; Li et al., 2022). Lin and Tan (2017), Li et al. (2017) and Zhou et al. (2022), respectively, set up different scenarios to analyze the effects and calculate the carbon emissions of China's energy intensive industries. Regarding the research on the carbon peak time, Wang et al. (2019) conducted scenario analysis of carbon emissions in China's industrial sector and concluded that the peak time of each industrial sub-sector is different, while Cui et al. (2021) explored whether ten coastal provinces can meet their carbon emission peak targets by 2050. These studies about scenarios analysis mainly focus on different sub-sectors in China and few was for the manufacturing industry. In addition, there are also great differences in carbon peaking policies in different regions, so it is necessary to study by regions.

3 Methods

3.1 Kaya identity and LMDI

The LMDI decomposition analysis can estimate the impact of each candidate factor on carbon emissions (Ang & Goh, 2019; Ang & Zhang, 2000; Xu & Ang, 2013). This method has the advantage of residual-free and aggregation-accurate (Ang, 2004). According to Kaya identity, we first decomposed carbon emissions into eight influencing factors. The specific model is as follows:

$$
\begin{aligned}
C &= \sum_r \sum_j P_r \left(\frac{PU_r}{P_r} \right) \left(\frac{GDP_r}{PU_r} \right) \left(\frac{IV_r}{GDP_r} \right) \left(\frac{E_r}{IV_r} \right) \left(\frac{E_{jr}}{E_r} \right) \left(\frac{C_{jr}}{E_{jr}} \right) \\
&= P \cdot U \cdot M \cdot V \cdot R \cdot S \cdot F
\end{aligned} \tag{1}
$$

where C is carbon emissions; P_r is total population by the rth province; PU_r is urban population by the rth province; GDP_r is total GDP by the rth province; IV_r is manufacturing fixed asset investment scale by the rth province; E_r is fossil energy consumption by the rth province; E_{jr} is the energy consumption of the jth fossil energy source (coal, oil, natural gas) by the rth province; C_{jr} is carbon emissions from jth fossil energy source by the rth province; $U = \frac{PU}{P}$ is urbanization rate; $M = \frac{GDP}{PU}$ is economic development; $V = \frac{IV}{GDP}$ is investment share; $R = \frac{E}{IV}$ is energy intensity; $S = \frac{E_j}{E}$ is the proportion of energy consumption of three fossil energy sources; $F = \frac{C_j}{E_j}$ is carbon emission factors of three fossil energy sources, which can be regarded as a constant.

Because some previous studies have confirmed that investment has a driving effect on energy consumption and the manufacturing economy (Fu et al., 2014), but few studies focused on the impact of investment effects on carbon emissions, we introduce V and R here to study the role of investment in manufacturing carbon emissions.

The additive decomposition method proposed by Ang et al. (2015) for energy consumption can further quantify the impact of factors on carbon emissions. The overall effects are formulated as follows:

$$\Delta C = C^t - C^0$$
$$= \Delta C_P + \Delta C_U + \Delta C_M + \Delta C_V + \Delta C_R + \Delta C_S \tag{2}$$

ΔC is the total change of carbon emissions and the right-hand side of the equation gives the effects associated with the eight factors between the years t and 0. The general formulas of LMDI for the effect of each factor can be defined as:

$$\Delta C_i = \sum \frac{C^t - C^0}{\ln(C^t - C^0)} \times \ln\left(\frac{i^t}{i^0}\right) \tag{3}$$

where i represent eight influencing factor variables.

According to the studies in Table S1, the population effect, urbanization effect, and economic development effect usually play a role in promoting carbon emissions as the growth of these variables requires energy consumption and causes emissions, while the energy structure plays a weak inhibitory role as the increased proportion of clean energy can relieve carbon emissions. The impact of investment on carbon emissions may be achieved by promoting economic development and energy consumption, which is needed to be confirmed by analyzing the effects of V and R.

3.2 Decoupling index

The decoupling index (DI) is used to illustrate the environmental burden of investment growth. Based on the elastic coefficient method, Tapio (2005) define the decoupling state with the range of elastic value. It is also widely used in the field of economic growth, resources, and environment. It can be presented as:

$$D = \frac{\%\Delta C}{\%\Delta V} \tag{4}$$

where $\%\Delta C$ indicates the growth rate of carbon emissions per capita and $\%\Delta V$ is the growth rate of fixed asset investment in manufacturing. It can be calculated year on year or as an average annual growth rate in a given period. The eight different decoupling state is listed in Table 1.

Decoupling state generally means the situation when the growth of carbon emissions is lower than the investment. It indicates that the dependence of investment growth on carbon emissions is weakening. However, it doesn't mean the manufacturing industry has achieved

Table 1 Criteria for the classification of decoupling indicator

The value of D	The value of GDP and C	Decoupling state
$D < 0$	$\%\Delta V > 0, \%\Delta C < 0$	Strong decoupling
	$\%\Delta V < 0, \%\Delta C > 0$	Strong negative decoupling
$0 < D < 0.8$	$\%\Delta V > 0, \%\Delta C > 0$	Weak decoupling
	$\%\Delta V < 0, \%\Delta C < 0$	Weak negative decoupling
$0.8 < D < 1.2$	$\%\Delta V > 0, \%\Delta C > 0$	Expansive coupling
	$\%\Delta V < 0, \%\Delta C < 0$	Recessive coupling
$D > 1.2$	$\%\Delta V > 0, \%\Delta C > 0$	Expansive negative decoupling
	$\%\Delta V < 0, \%\Delta C < 0$	Recessive decoupling

low carbon, and it just represents that the correlation between carbon emissions and investment has been cut off, which is one of the steps to achieve low-carbon development.

3.3 Scenario design

Based on the LMDI decomposition analysis, the emissions in manufacturing sectors in the year t can be estimated by the changes of population (P), urbanization rate (U), economic development (M), investment share (V), energy intensity (R), the proportion of energy consumption (S), carbon emission factors (F) to the base year. Thus, based on Eq. (1), we develop three scenarios, including baseline scenario (BS), low scenario (LS), and high scenario (HS), to project the provincial emissions in manufacturing sectors in China up to 2035. Since China's Five-Year Plan (FYP) implements development targets and policy strategies to guide the direction of economic and social development, the projected periods are divided into three time periods, including 2019–2025, 2026–2030, 2031–2035. In the Baseline scenario, the annual average growth rates (AAGRs) of population (P), urbanization rate (U), economic development (M) and energy intensity (R) and the proportion of energy consumption (S) are estimated in accordance with the FYPs of each province and related historical trend. (The details of references can be seen in Table S1.) During 2026–2030 and 2031–2035 without FYPs, we estimate AAGRs with their development trends and government policies. For example, we assume that S_3 will keep the same speed with a 4% AAGR during 2019–2025 in Beijing. From 2025, the proportion of energy consumption of natural gas will continue to grow. Thus, the AAGR for S_3 during 2026–2030 and 2031–2035 will be 1.0 and 2.0 percent higher than that during 2018–2025, respectively. Each variable prediction method of each province is similar to this, and the growth values are adjusted according to different AAGRs in 2019–2025. In the high and low scenarios, referring to Song et al. (2022), we adjust the AAGRs from the baseline scenario for a comparison analysis. The HS refers to the largely adopted mitigation measures (e.g., reduce energy intensity and adjust energy structure) when economic and social development was exponential. Conversely, the LS only achieves a slow development of economic and social development with relatively loose environmental regulation. The detailed assumptions of the AAGRs of population (P), urbanization rate (U), economic development (M) and energy intensity (R) and the proportion of energy consumption (S) over 2021–2035 in three scenarios are given in Tables S2, S3, S4, S5 and S6.

Since China's FYP did not provide the target of investment share during 2021–2035, we estimate the AAGRs of investment share (V) based on the AAGRs of investment and GDP scale. Since the investment scale of manufacturing sectors for 30 provinces for the period of 2021–2035 could not be directly obtained based on the China's FYPs, future provincial total fixed asset investment is available from the FYPs. We assumed that a 1% increase of total fixed asset investment would lead to a specific percentage increase of the investment in manufacturing industry and estimate the elasticities of investment scale based on the function of total fixed asset investment in 30 provinces.

Since the scenario analysis is a static projection which ignores the possible uncertainties in the future, based on the above scenarios, we employ the Monte Carlo simulation method to project China's overall and provincial manufacturing carbon emissions, such that the possible ranges of future emissions can be obtained by considering the uncertainties of driving factors. We first define prior probabilities for future change rates of factors as the triangular distribution, as the most expected value and the range for each factor can be pre-estimated by the above scenario design. Then, we conduct 10,000 Monte Carlo simulations

such that accurate results can be obtained. Finally, we take the results of the maximum value, minimum value and the middle value under the 5% confidence interval to obtain the forecast curves of China's manufacturing carbon emissions from 2019 to 2035 under the three scenarios, and the proportion of manufacturing carbon emissions in every five years is obtained according to the total carbon emissions data of China predicted by IEA.

3.4 Data source

In our paper, the provincial total population, urban population and GDP data are extracted from each provincial statistical yearbook (2003–2018). We collect provincial fixed asset investment data from Statistical Yearbook of the Chinese Investment in Fixed Assets (2003–2018). The energy consumption of the three types of fossil fuels in the manufacturing industry from 2003 to 2018 is obtained from CEADs; then, we use carbon emission factors of different energy sources in Guidelines for Compiling Provincial Greenhouse Gas Inventories to calculate the corresponding carbon emissions. Thirty provinces are included, expect for Tibet, Taiwan, Hong Kong, and Macao because of the lack of data.

4 Results

4.1 Drivers of manufacturing emissions

The carbon emissions in China during the 2003–2018 period can be divided into four stages, with 2007, 2013, and 2016 as the nodes according to the turning point of the changing curve of China's carbon emissions (see Fig S1). Figure 1 reflects the decomposition of manufacturing carbon emissions of these four stages in China. Based on LMDI method, the
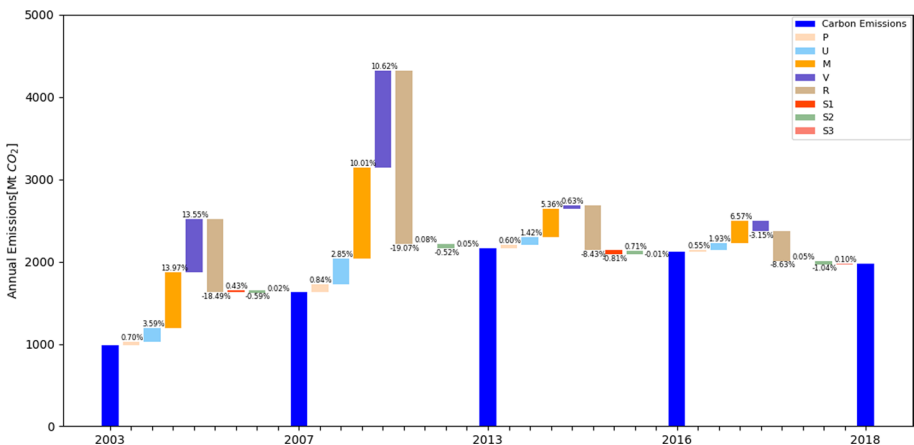
Fig. 1 Drivers of manufacturing emissions in China during 2003–2018. Note: as the number of years is not the same in both periods, we display compound annual growth or reduction. The compound annual rate of total emissions (r) is related to the total rate (R) across n years as $r = \sqrt[n]{(1 + R)}\text{-}1$, and compound annual contribution of a given factor (k) is $r \times S_k$ where S_k is the share of the contribution of the factor during the whole period

contribution of nine drivers to China's manufacturing carbon emissions is analyzed. The factors include population, urbanization, economic development, investment share, energy intensity and the proportion of energy consumption in three types of fossil energy source (coal, oil, and natural gas). In general, China's manufacturing carbon emissions increased from 2003 to 2013 and decreased 2013 to 2018, with the annual growth rate of 13.28% year^{-1}in 2003–2007, compared with -3.61% year^{-1} in 2016–2018. Figure 1 shows investment share and economic development were the main drivers of carbon emission growth, while energy intensity played an important role in carbon reduction. The population factor, urbanization factor and economic development factor played a positive role from 2003 to 2018, and among them economic development factor dominated, stemming from China's fast-growing GDP, although its proportion decreased gradually. The proportion of population factor fluctuated around 0.6%, while the urbanization factor decreased from 3.59 to 1.93% year^{-1}. Due to national economic policy that focus on investment ten years ago and its slowing growth in recent years, investment share accounted for 13.55% year^{-1} in 2003–2007, falling to 10.62% year^{-1} in 2007–2013 and 0.63% year^{-1} in 2013–2016, and then even dropped to -3.15% year^{-1} in 2016–2018, which played a role in reducing carbon emissions. Energy intensity had a reducing effect on carbon emissions, from -18.49% year^{-1} in 2003–2007 to -19.07% year^{-1} in 2007–2013, -8.43% year^{-1} in 2013–2016 and -8.63% year^{-1} in 2016–2018. It has the largest share of all factors due to the government's emphasis on reducing energy intensity. The effect of S_j (the energy consumption proportion of three fossil energy sources) was negligible, no more than 1% year^{-1} in all four stages. Because the country pay attention to the development of clean energy these years, energy consumption of natural gas continued to grow positively while coal and oil grow negatively.

Then, the drivers for each province are also analyzed. Figure 2 shows that investment, economic development and energy intensity were the main influencing factors, which was similar to the national level. Population played a positive role in manufacturing carbon emissions in each province, but the contribution rate was small, which was no more
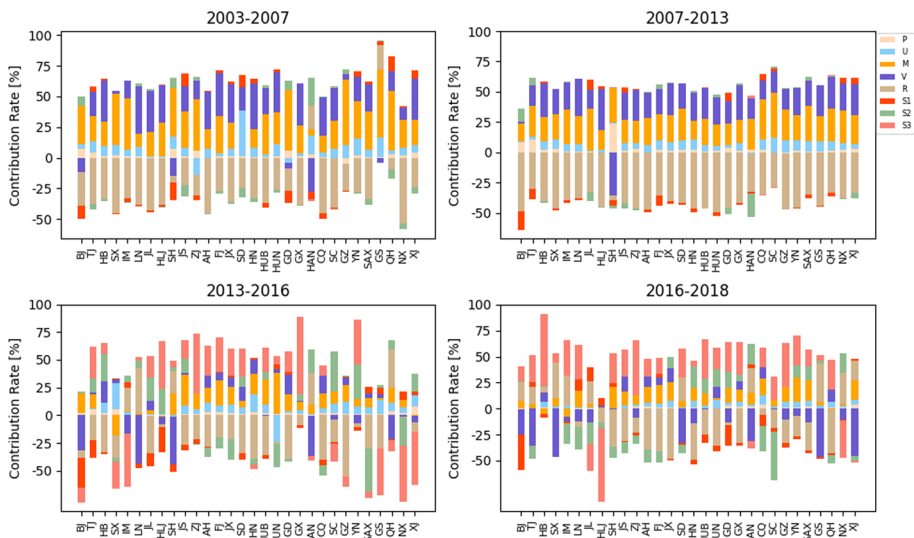

Fig. 2 Drivers of manufacturing emissions in 30 provinces during 2003–2018

than 0.1 in almost all provinces. Urbanization led to an increase in manufacturing carbon emissions in all provinces except Zhejiang, Guangdong, in 2003–2007 and Hunan in 2013–2016. Corresponding to Fig. 1, economic development played a significant role in promoting emissions in all provinces before 2013, accounting for about 0.2–0.4 year^{-1}, after 2013, it dropped to less than 0.2 year^{-1} and even became negative in some provinces. With the proportion close to economic development, the investment share was the main driver in promoting emissions in all provinces except Beijing and Shanghai before 2013, while after 2013, consistent with the national level, it played a role in reducing emissions in most provinces with the value of contribution rate was around -0.3 to -0.1 year^{-1}. The main force in reducing carbon emissions in provinces was energy intensity, while its contribution rate in most provinces was around -0.2 to -0.4 year^{-1}. After 2013, as provinces promoted clean energy in recent years to reduce carbon emissions, the proportion of natural gas energy consumption in three fossil energy sources became the main driving force with the value increasing to 0.2 and 0.5 year^{-1}, compared with its weak effect before 2013 with no more than 0.01 year^{-1}. Coal and oil had a positive impact in most provinces, except Beijing's share of coal always had an impact on reducing emissions, but these two factors' impacts had gradually become insignificant.

4.2 Decoupling of manufacturing emissions from investment growth

Based on Eq. (4), the DI of China's manufacturing carbon emissions from investment scale during the time 2004–2018 was calculated and the decoupling status for each year was defined. As shown in Fig. 3, the status before 2013 and in 2014 was weak decoupling. In the status of weak decoupling, China's manufacturing carbon emissions and investment were both increasing, but investment grew faster than carbon emissions. DI fluctuated around 0.2 from 2007 to 2012 and became negative for the first time in 2013 due to a reduction in manufacturing carbon emissions. In 2015, the status turned to weak
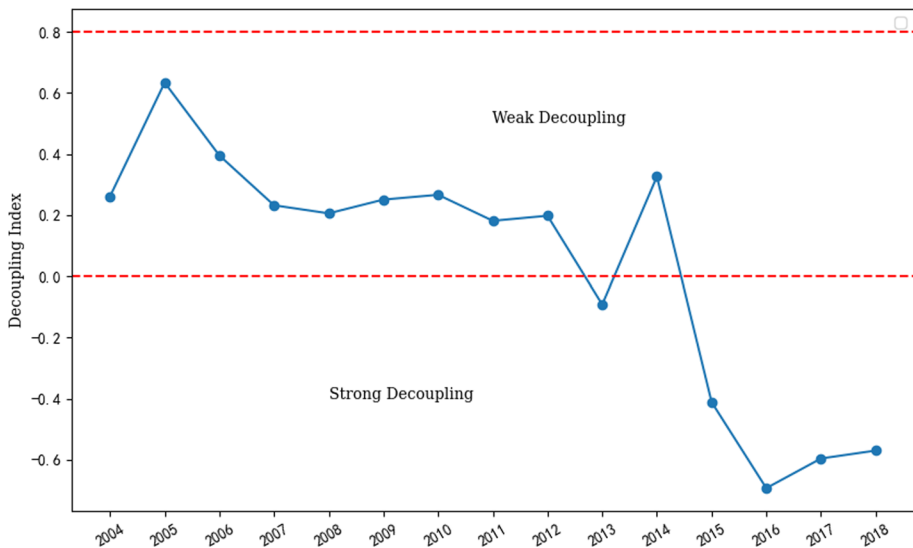

Fig. 3 Decoupling of manufacturing emissions from investment scale in China during 2003–2018
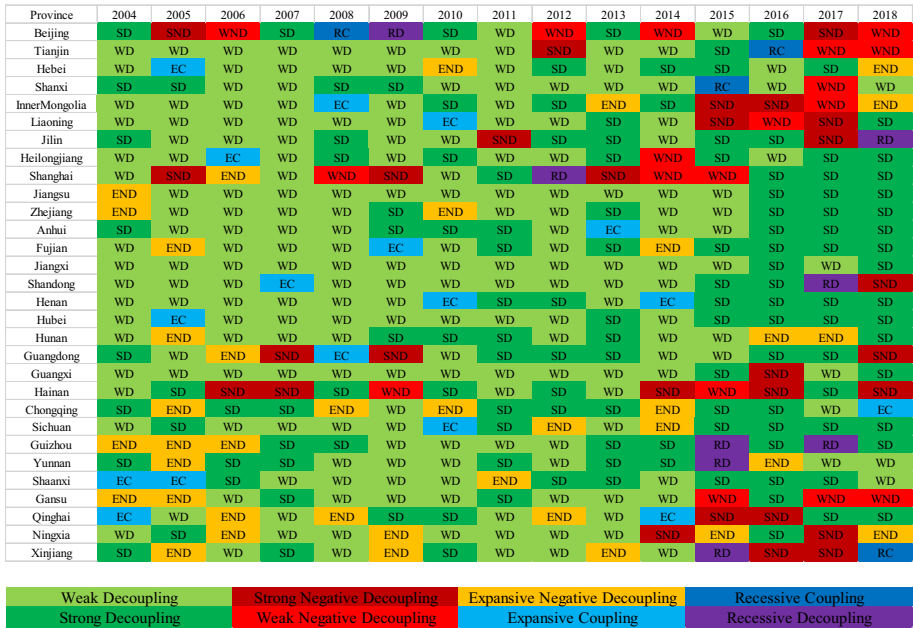
Province	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
Beijing	SD	SND	WND	SD	RC	RD	SD	WD	WND	SD	WND	WD	SD	SND	WND
Tianjin	WD	WD	WD	WD	WD	WD	WD	WD	SND	SD	WD	SD	RC	WND	WND
Hebei	WD	EC	WD	WD	WD	WD	END	WD	SD	WD	SD	SD	WD	SD	END
Shanxi	SD	SD	WD	WD	SD	SD	WD	WD	WD	WD	WD	RC	WD	WND	WD
InnerMongolia	WD	WD	WD	WD	EC	WD	SD	WD	SD	END	SD	SND	SND	WND	END
Liaoning	WD	WD	WD	WD	WD	WD	EC	WD	WD	SD	WD	SND	WND	SND	SD
Jilin	SD	WD	WD	WD	SD	WD	WD	SND	SD	SD	WD	SD	SD	SND	RD
Heilongjiang	WD	WD	EC	WD	SD	WD	SD	WD	WD	SD	WND	SD	WD	SD	SD
Shanghai	WD	SND	END	WD	WND	SND	WD	SD	RD	SND	WND	WND	SD	SD	SD
Jiangsu	END	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	SD	SD	SD
Zhejiang	END	WD	WD	WD	WD	SD	END	WD	WD	SD	WD	WD	SD	SD	SD
Anhui	SD	WD	WD	WD	WD	SD	SD	SD	WD	EC	WD	WD	SD	SD	SD
Fujian	WD	END	WD	WD	WD	EC	WD	WD	WD	SD	END	SD	SD	SD	SD
Jiangxi	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	SD	SD	WD	SD
Shandong	WD	WD	WD	EC	WD	WD	WD	WD	WD	WD	WD	SD	SD	RD	SND
Henan	WD	WD	WD	WD	WD	WD	EC	SD	SD	WD	EC	SD	SD	SD	SD
Hubei	WD	EC	WD	WD	WD	WD	WD	WD	WD	SD	WD	SD	SD	SD	SD
Hunan	WD	END	WD	WD	SD	WD	SD	SD	WD	WD	WD	WD	END	END	SD
Guangdong	SD	WD	END	SND	EC	SND	WD	SD	SD	SD	WD	WD	SD	SD	SND
Guangxi	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	WD	SD	SND	WD	SD
Hainan	WD	SD	SND	SND	SD	WND	WD	SD	WD	WD	SND	WND	SND	SD	SND
Chongqing	SD	END	SD	SD	END	WD	END	SD	SD	SD	END	SD	SD	WD	EC
Sichuan	WD	SD	WD	WD	WD	WD	EC	SD	END	WD	END	SD	SD	SD	SD
Guizhou	END	END	END	SD	SD	WD	WD	WD	SD	SD	SD	RD	SD	RD	SD
Yunnan	SD	END	SD	SD	SD	WD	WD	SD	WD	SD	SD	RD	END	WD	WD
Shaanxi	EC	EC	SD	WD	WD	WD	WD	END	SD	SD	WD	SD	SD	SD	WD
Gansu	END	END	SD	SD	WD	WD	WD	SD	WD	WD	WD	WND	SD	WND	WND
Qinghai	EC	WD	END	WD	END	SD	SD	WD	END	WD	EC	SND	SND	SD	SD
Ningxia	WD	SD	END	WD	WD	END	WD	WD	WD	WD	SND	END	SD	SND	END
Xinjiang	SD	END	WD	SD	WD	END	SD	WD	WD	END	WD	RD	SND	SND	RC

Weak Decoupling · Strong Negative Decoupling · Expansive Negative Decoupling · Recessive Coupling
Strong Decoupling · Weak Negative Decoupling · Expansive Coupling · Recessive Decoupling

Fig. 4 Decoupling of manufacturing emissions from investment scale in 30 provinces during 2003–2019

Table 2 Regional classification

Regional division	Provinces
North China	Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia
Northeast China	Liaoning, Jilin, Heilongjiang
East China	Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong
Central South China	Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan
Southwest China	Chongqing, Sichuan, Guizhou, Yunnan
Northwest China	Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang

decoupling again, but then, the DI remained negative for the next four years, that is, strong decoupling. Overall, before 2013 and after 2014, the decoupling state remained stable, which is inseparable from the energy saving and emission reduction policy started during the 11th FYP period. The change of DI from weak decoupling to strong decoupling shows that China's manufacturing industry has achieved remarkable results in reducing carbon emissions and sustainable development.

According to Eq. (4) and the categories given in Table 1, the decoupling status of 30 provinces from 2004 to 2018 was classified as shown in Fig. 4. The table in Fig. 4 shows the variation of the eight categories over the analyzed period in 30 provinces in China, where each of the eight decoupling categories is represented by a unique color. According to Li (2020), divide six regions of China (see Table 2) to analyze this table. In 2004–2014, the decoupling status of North China and Northeast China was dominated by WD and SD; then, the main status of North China was SD and WND in 2015–2018, while Northeast

China was SD and SND at the same time. The unstable changes in the state represent that these two regions have not yet reached a complete decoupling state, maybe because these two regions are still the industry structure led by heavy industries. The decoupling status of East China and Central South China in 2004–2015 was dominated by WD, and in 2016–2018 SD became the main status in these two regions. The decoupling state is basically stable, which has a lot to do with the continuous implementation of the low carbon economic policy and the industrial structure dominated by the service industry and light industry in these two regions. Before 2015, both Northwest China and Southwest China had WD as the main status, followed by SD and END, then after 2015, the decoupling status was rich in various types, with SD as the main status, and RD, WND, WND and other types appeared. These variable states are attributed to the Western Development strategy in these provinces. It is worth mentioning that when other provinces changed between three or four types, Beijing, and Shanghai, as the two core economic provinces, had six types of decoupling status from 2004 to 2018, and the status is constantly changing, which is related to the changing economic and low carbon policies of the two major cities. Moreover, after 2015, the main decoupling status in economically developed areas (e.g., Zhejiang, Shanghai, and Guangdong) was SD, while in economically underdeveloped areas (e.g., Hainan and Gansu) the status of SND, WND, RC, and RD had appeared in recent years. This means that the proportion of industrial output in the economically underdeveloped province is still growing rapidly, so it is difficult to reduce carbon emissions.

4.3 Projections of manufacturing emissions

Figure 5 shows the projected changes in China's manufacturing carbon emissions from 2019 to 2035 under three scenarios and the projected proportion of manufacturing carbon emissions in the country's carbon emissions. Figure 5 shows that in the High scenario, China's manufacturing carbon peak will be reached with 2403 Mt CO$_2$ in 2030, which is the target year. Then in 2030–2035, manufacturing carbon emissions will be reduced to 2393 Mt CO$_2$. But in the other two scenarios, the projected carbon emissions will continue to grow until 2035, peaking at 3489 Mt CO$_2$ in the Baseline scenario and 4648 Mt CO$_2$ in the Low scenario. In all three scenarios, the proportion of manufacturing carbon emissions to national carbon emissions (data from IEA forecasts) will peak in 2030 at 24.45, 31.61 and 38.78% in the High, Baseline and Low scenarios, respectively.

Figure 6 shows the possible change of provincial manufacturing carbon emissions up to 2035 in all three scenarios. It can be seen that all provinces have the highest carbon emissions in the Low scenario and the lowest carbon emissions in the High scenario. Therefore, we can know that the increase in the population, urbanization rate, economic development, and the proportion of energy consumption of natural gas does not promote carbon emissions enough to compensate for the inhibition of carbon emissions caused by the decrease in investment share, energy intensity and the proportion of coal and oil.

The change trends of the projections of manufacturing carbon emissions vary in different provinces. It's on a downward trend in the Northeast China and Northwest China like Liaoning, Qinghai, Ningxia and Xinjiang, and an upward trend in the East China and Southwest China like Jiangsu, Zhejiang, Fujian, Chongqing and Yunnan. Manufacturing carbon emissions in major energy provinces such as Shandong still shows a strong upward trend. There were also two different trends in the Low scenario and High scenario in some provinces like Tianjin, Hebei, Henan, Sichuan, Shaanxi and Gansu, which explains the difference in the curve trends of these two levels across the country. Most of the southern
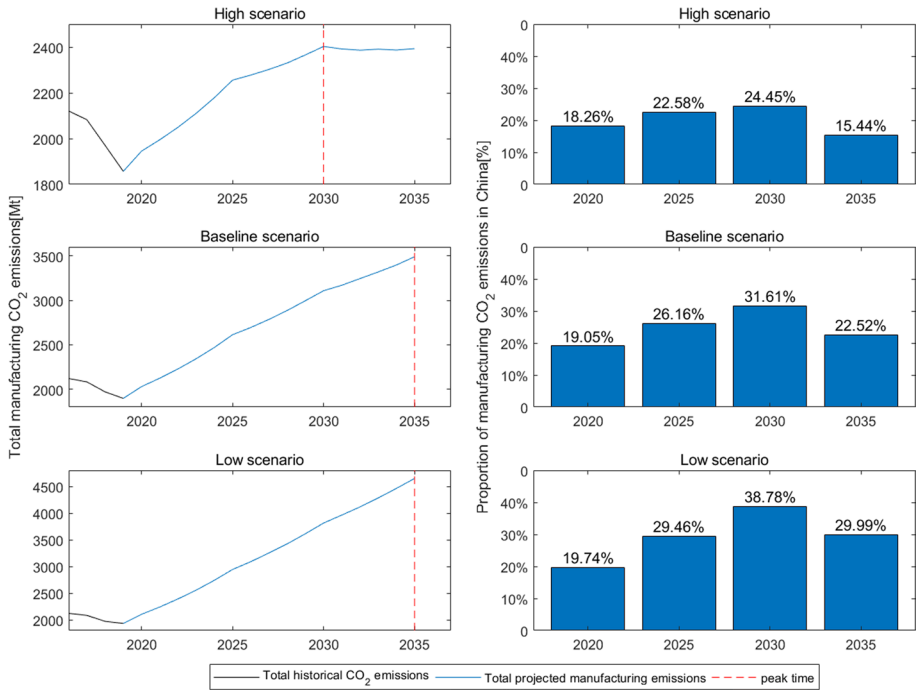
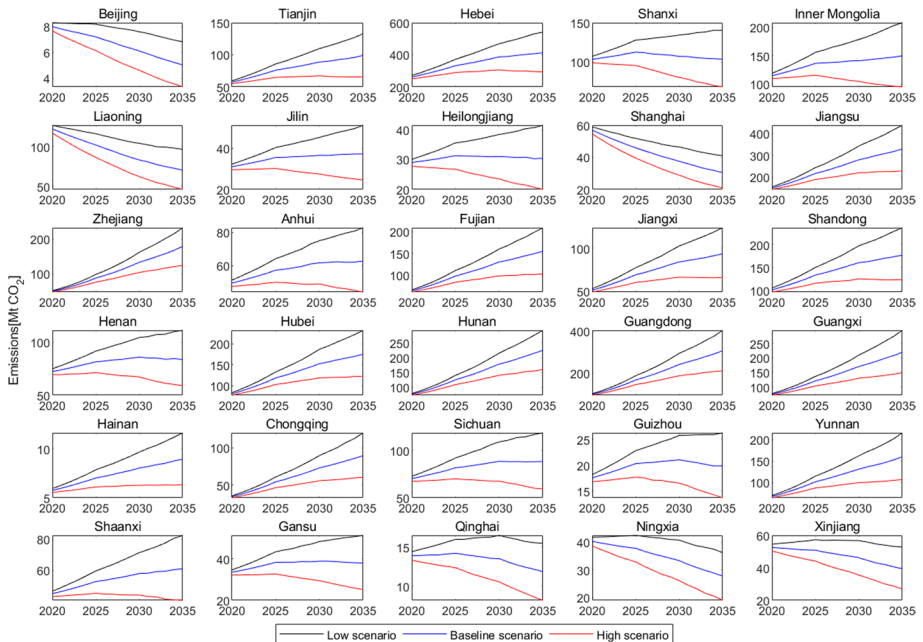**Fig. 5** Projections of manufacturing emissions in 30 China during 2020–2035

Fig. 6 Projections of manufacturing emissions in 30 provinces during 2020–2035

regions have a high level of economic development and less pollution, so it is predicted that the trend of manufacturing carbon emissions will continue to rise in the future, while the northern region is the opposite, so it will show a downward trend. It is worth mentioning that some developed provinces, such as Jiangsu, Zhejiang, Guangdong, are difficult to achieve the target of peaking emissions by 2030. From the perspective of driven factors, these provinces have developed economy and high economic development goals, so the urbanization rate and economic development effect are very strong. From the perspective of economic structure, the manufacturing industry of these provinces is dominated by light industry, while China mainly focuses on heavy industry emissions reduction, which may ignore the emission reduction of these provinces' industry. From a policy perspective, these provinces are close to or contain super-first-tier cities, so there are cases of factory relocation.

Therefore, from the analysis of Fig. 6, we can divide the 30 provinces into three categories (see Table 3):

(1) Provinces which can meet the peak emissions target in 2030. Beijing, Liaoning, Shanghai, Guizhou, Qinghai, Ningxia, and Xinjiang are fall into this category, accounting for 23.33% of 30 provinces, because these 7 provinces can reach their MCE peaks before 2030 in all three scenarios. If these provinces can stick to their current emission reduction policies and rein in MCE growth, the 2030 target will be easily achieved.

(2) Provinces which are likely to peak in emissions before 2030. For such provinces, peaking before 2030 can only be achieved only in one or two scenarios. 15 provinces including Tianjin, Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Shandong, Henan, Hubei, Hainan, Sichuan, Shaanxi, and Gansu belong to this category. The change trends in these provinces differ widely across three scenarios. For example, Hebei can only meet its 2030 emission target in the High scenario. In the Low scenario, it shows an increasing trend. This means that current emissions control measures are insufficient to support these provinces in reaching their targets. The government has stepped up efforts to effectively balance manufacturing consumption and energy consumption, which is very helpful to achieve the emission reduction target of manufacturing.

(3) Provinces which are difficult to achieve the target of peaking emissions by 2030. Eight provinces including Jiangsu, Zhejiang, Fujian, Hunan, Guangdong, Guangxi, Chongqing, and Yunnan belong to this category. These provinces are unable to peak emissions before 2030, and in all three scenarios, emissions continue to increase through 2035.

Table 3 Provinces classification according to the possibility to meet 2030 carbon peak

The possibility to meet 2030 carbon peak	Provinces
Can	Beijing, Liaoning, Shanghai, Guizhou, Qinghai, Ningxia, and Xinjiang
Likely	Tianjin, Hebei, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Shandong, Henan, Hubei, Hainan, Sichuan, Shaanxi, and Gansu
Difficult	Jiangsu, Zhejiang, Fujian, Hunan, Guangdong, Guangxi, Chongqing and Yunnan

Therefore, there is a need for further push by provincial governments to control the growth of MCE, such as reducing the energy intensity of manufacturing and the use of fossil fuels.

5 Conclusions and policy implications

5.1 Conclusions

In this paper, we first investigated the drivers of China's manufacturing emissions using the LMDI model. Then, we analyzed the decoupling relationship between manufacturing investment and carbon emissions at the national and provincial levels. Finally, we employ the scenario analysis to project the future change of manufacturing carbon emissions across the country and each province in different scenarios to observe the possible peak time. The main conclusions are as follows:

(1) At the national level, the annual growth rate of manufacturing carbon emissions gradually decreased, from 13.28% in 2003–2007 to −3.61% in 2016–2018. The energy intensity effect contributed the most in reducing the manufacturing carbon emissions during the whole study period. The economic development was the most powerful effect promoting manufacturing carbon emissions in 2003–2007 and 2007–2013, then followed by investment share in 2013–2016 and 2016–2018. This is caused by China's rapidly growing GDP and the government's emphasis on reducing energy intensity.

(2) At the provincial level, the economic development and investment share played the most powerful role in increasing manufacturing carbon emissions in most provinces in the two time periods of 2003–2007 and 2007–2013, while the energy intensity was the major factor of reducing emissions. Then in 2013–2016 and 2016–2018, the investment share played a role in reducing emissions with the −0.3 to −0.1 year^{-1} contribution rate. The main promotion effect in the last two time periods was the proportion of natural gas energy consumption in three fossil energy sources as most provinces have vigorously developed clean energy in recent years, which was the biggest difference compared with the national level.

(3) During the study period, the decoupling status of manufacturing carbon emissions and investment scale at the national level gradually changed from weak decoupling in 2004–2014 to strong decoupling in 2015–2018, which is due to the national emission reduction policy. At the provincial level, the decoupling status of almost all provinces before 2015 was dominated by WD. After 2015, the decoupling status varies by regions, while the main decoupling status in economically developed areas was SD and in economically underdeveloped areas the status of SND, WND, RC and RD had appeared due to the development policies and industrial structures of different regions.

(4) In the scenario analysis, at the national level, the manufacturing carbon emissions can reach the peak emissions before 2030 with 2403 Mt CO_2 in the High scenario while in Baseline and Low scenarios the projected emissions keep grow until 2035. At the provincial level, based on the peak time of manufacturing carbon emissions in each province, 30 provinces are divided into three categories. In all three scenarios, 7 provinces can reach their emissions peak before 2030, fifteen provinces need more help to

meet their 2030 emissions targets for the manufacturing and there are still 8 provinces that will not reach peak manufacturing carbon emissions by 2030. This is related to the economic development, industrial structure, and policies of different provinces, so the focus of the policies to reduce the manufacturing carbon emissions should be adjusted according to different provinces.

5.2 Policy implications

Based on the results, we suggest that the government can take some policies for manufacturing to achieve the goal of carbon peak. The specific policies are as follows:

(1) Encourage the transformation of manufacturing to improve the efficiency of energy utilization.

     Through LMDI decomposition analysis, the investment share and the energy intensity were the most important factors in the carbon emissions increase and reduction, respectively. Therefore, the government should introduce relevant policies should be introduced to encourage the low carbon transformation of the manufacturing industry to guide enterprises to increase investment in technological transformation. Further, energy conservation and new energy technology can be vigorously developed to improve the utilization efficiency of energy. It's also necessary to reduce the role of economic development reasonably and appropriately in promoting carbon emissions, such as curbing the blind development of industries with low levels, high energy consumption and high emissions.

(2) Optimize investment structure according to regions' decoupling situation.

     After 2015, the economically developed regions have achieved strong decoupling between the investment and carbon emissions, while the decoupling status of economically underdeveloped regions was diversified. Thus, those underdeveloped regions are required to further increase investment distribution in future policy formulation, and make efforts to optimize the investment structure, such as increasing investment in new energy technologies and reducing unnecessary use of energy-intensive industrial sites.

(3) Adjust the current emission reduction policies in the light of the provincial conditions.

     According to results of scenario analysis, the emissions peak of seven provinces can be reached before 2030, thus, they should continue to maintain the provincial planning of the current policy. For eight provinces those cannot reach the peak before 2030, they need the government to further provide emission reduction power according to their own the geographical environment, resources, and other characteristics, for instance, Hunan can make more use of water resources and further increase the proportion of clean energy based on the abundance of local water resources. For the remaining provinces which are likely to reach 2030 carbon peaks, they should strictly reduce energy intensity and adjust energy structure according to the government setting goals.

Availability of data and materials The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request. All data generated or analyzed during this study are included in this published article (and its supplementary information files).

Declarations

Conflict of interest The authors have no relevant financial or non-financial interests to disclose.

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