



# Decomposition and scenario analysis of final demand embedded manufacturing consumption emissions: insights from the province-level data

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## Abstract

In order to support the emissions reduction options in manufacturing industry effectively, it is necessary to quantify the final demand embedded manufacturing consumption (DEMC) emissions which can be estimated by converting intermediate manufacturing consumption into all final demand categories. Here, we quantify the DEMC emissions in China's 30 provinces during 2007–2017 using a multi-regional input–output (MRIO) model and the modified hypothetical extraction method (HEM). Then, we analyze impacts of four factors (including emissions multipliers, consumption structure, investment efficiency, and investment scale) on the DEMC emissions. Finally, considering a large driving effect of investment scale on manufacturing emissions, we conduct four scenarios to quantify the mitigation potential of DEMC emissions during 2020–2035. We find that from 2007 to 2012, the DEMC emissions increased doubled, while during 2012–2017, it decreased from 1217 to 634 Mt. The capital-intensive manufacturing and the labor-intensive manufacturing industries were main sources of intra- and inter-sectoral emissions, respectively. Investment scale was the main driver of the growth in DEMC emissions during 2007–2015, while it led to a reduction of DEMC emissions during 2015–2017. Emission multipliers had the largest positive impact on the reduction of DEMC emissions during the whole period. Consumption structure increased DEMC emissions during 2007–2012, while with the consumption structure shift towards knowledge-intensive manufacturing industry, it induced a reduction of DEMC emissions during 2012–2017. Moreover, implementing an integrated mitigation measures (including reducing emissions multipliers, decreasing investment efficiency, and adjusting consumption structure) could help China to realize the emissions peaking target. However, there are still 8 provinces whose DEMC emissions are unlikely to peak before 2030.

**Keywords** Multi-regional input–output model · Hypothetical extraction method · LMDI · Final demand embedded manufacturing consumption emissions · Scenario analysis

## Introduction

The manufacturing industry has become an important driver of economic growth in China, representing 27.4% of the total GDP in 2021 (Statista 2022). Due to emission-intensive production, the manufacturing industry consumed 56.2%

of the total energy consumption in 2020 (CSY 2021) and produced 66% of the total emissions in 2016 (Meng et al. 2021). China proposed to reduce carbon emissions per unit of GDP by 40% by 2025 compared with the 2015 level, according to the manufacturing power strategy “Made in China 2025” (Chen et al. 2021). Thus, how to reasonably reduce manufacturing emissions in China is an important factor that impacts China's emissions mitigation goal (Yang et al. 2018). According to the 14th Five-Year Plan and White Paper on High-quality Development and Industrial Policy Transformation in the Manufacturing Industry during the 14th Five-Year Period, the value-added of China's manufacturing sector will account for 30% of GDP in 2030; thus, the emissions share of manufacturing industry is likely to continue to rise. This means that the contradiction between

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the development of China's manufacturing industry and carbon emissions reduction is increasingly prominent (Hang et al. 2019).

Since manufacturing production activities cause large emissions (Liu 2015; Grasso 2016; Afonis et al. 2017), much attention is paid to improve productive efficiency of manufacturing industry (Lee 2021; Meng et al. 2021; Vieira et al. 2021). For example, Yang et al. (2020) used the Data Envelopment Analysis approach to calculate the emissions efficiency and reduction potential of the manufacturing industry in China's 30 provinces. Lan et al. (2021) analyzed spatial effects of manufacturing agglomeration modes on provincial emissions. Yang et al. (2021) explored the relationship between manufacturing growth and emissions using a finite mixture model. However, the shared responsibility principle for emissions highlights that the emissions can be mitigated effectively by the consumption-based accounting (CBA) approach (Davis and Caldeira 2010; Hertwich 2021; Zhang et al. 2021). This is because the CBA considers the linkages of sectoral CO<sub>2</sub> emissions (Wang et al. 2013; Kucukvar et al. 2016; Dong et al. 2022). As the production of manufacturing industry relies on the products from other industries, the emissions inevitably emit outside of the manufacturing industry for production (Sajid et al. 2021). Moreover, the CBA can build a relationship between emissions and final demand that is embodied in the economic system (Guan et al. 2008; Perobelli et al. 2015; Chen et al. 2018).

The input–output analysis (IOA) has been widely applied to explore sectoral emissions in China from the consumption perspective (Song et al. 2018; Zhang et al. 2018; Li et al. 2022; Ma et al. 2022; Wang et al. 2022a, b). Some researchers applied the IOA to the studies on China's manufacturing emissions (Tian et al. 2018; Zhang et al. 2020a; Zhou et al. 2021). Moreover, some studies investigated the factors affecting manufacturing emissions embodied final demand (Shao et al. 2017; Cao et al. 2019; Shao et al. 2020). These studies decomposed the driving factors into the emission intensity, energy intensity, energy structure, industrial activity, and industrial structure. They concluded that the expansion of output scale was the key driving factor of manufacturing emissions, and the reduction in energy intensity declined emissions. Nevertheless, they integrate the emissions from intermediate manufacturing production into different final demand categories (i.e., household, government, investment). This means that they consider the final demand of all sectors would together pull the intermediate manufacturing production. Thus, this approach only considers the emission intensities of the manufacturing sectors. Thus, using this approach, the emissions from intermediate manufacturing consumption are not embedded into various final demand types. Bai et al. (2018) and Sajid et al. (2020) concluded that reducing intermediate manufacturing

consumption is more effective for emissions mitigation than targeting manufacturing producers of emissions. This is because embedding intermediate manufacturing consumption emissions to final demand considers the emissions intensity of the upstream supply chain of the manufacturing industry, by isolating the intermediate and final consumption of manufacturing industry. Sajid et al. (2020) found that the total emissions embodied in final demand under the two procedures were the same; however, the allocation of emissions among the final demand of various industries is different. Thus, it is important to calculate the factors of final demand embedded manufacturing consumption (DEMC) emissions. Here, we define the DEMC emissions as the emissions from the intermediate manufacturing consumption which are embedded into final demand categories. We focus on the intermediate and final consumption of manufacturing industry and consider the emission intensities of the whole supply chain of manufacturing industry, such that the intermediate intra- and inter-sectoral consumption are both investigated.

The hypothetical extraction method (HEM) is a useful method to estimate intermediate carbon linkages (Zhou et al. 2016; Wang et al. 2021a; Hou et al. 2021). Using the HEM, the carbon linkages can be decomposed into the net forward, net backward, internal, and mixed intermediate carbon linkages (Guerra and Sancho 2010; Sajid et al. 2019a, 2021). Sajid et al. (2020) employed the HEM to analyze the emissions of intermediate industrial carbon linkages and divide the carbon linkage into inter-sectoral and intra-sectoral emissions. Sajid et al. (2021) further analyzed the driving factors of the final demand embedded industrial consumption emissions. However, most studies did not apply the HEM to Chinese Multi-Regional Input–Output (MRIO) tables. Thus, few studies analyzed the DEMC emissions at the provincial level.

Moreover, with the economic development and structure shift towards consumption in the “New Normal” period, the investment scale is slowing down, and the leading manufacturing industry tends to gradually transform from labor- and capital-intensive to technology-intensive manufacturing sectors (Li et al. 2019; Su et al. 2021; Wang and Han 2021). Also, the technological level might be improved with industrialization and the propose of emissions target (Shen and Lin 2020; Cheng et al. 2020). Those mean that manufacturing-related climate measures can contribute to future mitigation of DEMC emissions on the current investment change pathway. However, there lacks a comprehensive scenarios analysis of the mitigation potential of China's provincial DEMC emissions considering the possible changes of investment scale.

Here, our key contributions include three aspects: (1) previous research has used the IOA to study the manufacturing emissions embodied in the final demand at the national/regional level, but most studies only focused on the carbon

intensities of manufacturing sectors. We consider the emission intensities of sectors those distributed along the entire supply chain of manufacturing industry and embed the emissions from provincial intermediate manufacturing consumption into the final demand using the modified HEM and MRIO model. This provides a new perspective for analyzing the carbon linkage of China’s manufacturing industry. (2) Previous studies have investigated the driving factors of embedded emissions from the intermediate manufacturing production using the decomposition analysis (Tian et al. 2018; Liu et al. 2022; Xu et al. 2022). However, they did not analyze the driving factors of the DEMC emissions. Our analysis highlights the important contributions of emissions multipliers, consumption structure, investment efficiency, and investment scale to the DEMC emissions referring to previous studies on driving factors of manufacturing emissions (Hang et al. 2019; Cao et al. 2022). However, different from previous studies mostly focused on the driving factor analysis from production side, our study can help identify important driving factors of manufacturing emissions from the consumption side. (3) Previous studies have highlighted the large impact of investment on emissions (Li et al. 2021; Wang et al. 2021a, b). However, the mitigation potential of provincial DEMC emissions on the current investment change pathway is seldom explored. We develop four scenarios to explore the mitigation potential of DEMC emissions in 30 provinces. A reference scenario (Scenario REF) is used to explore the potential trajectory of DEMC emissions based on the current investment development pathway in 30 provinces. Three green development scenarios are constructed to test the effectiveness of three emissions reduction measures (i.e., emissions multiples reduction, consumption structure adjustment, and investment efficiency decrease). Such information will provide insights for reducing DEMC emissions on the current investment development pathway from a multi-provincial perspective.

The rest of the paper proceeds as follows. In Sect. 2, we present methods and information on the data. Section 3 provides the results. Section 4 present discussion, and Sect. 5 concludes the paper.

## Methods

In this study, we first define the DEMC emissions and analyze its pattern using the Chinese MRIO table, such that the DEMC emissions are decomposed into inter-sectoral and intra-sectoral emissions. Then, considering that LMDI method can provide specific size of driving factors, we apply the LMDI to analyze four driving factors (emission multipliers, consumption structure, investment efficiency, and investment scale) of the DEMC emissions. Finally, to analyze the future changes of DEMC emissions, we construct four scenarios (REF, EM,

CS, and IE scenarios) to evaluate the effectiveness of different emission mitigation measures, such that policy implications can be provided. The research flow chart is divided into three steps as shown in Fig. 1.

### Input–output model

The input–output model is usually used to analyze the input and output linkages across different sectors (Miller and Blair 2009). Based on the input–output research framework, an economy with  $n$  sectors is clarified as:

$$X = (I - A)^{-1}Y = LY \tag{1}$$

where  $X$  is the output vector;  $Y$  is the final demand vector;  $A$  is the direct consumption coefficients matrix with elements  $a_{ij} = \frac{x_{ij}}{x_j}$ ;  $I$  is the identity matrix;  $L$  is the Leontief inverse matrix, in which  $l_{ij}$  is the output of sector  $i$  that is directly and indirectly required to produce one unit of final demand from sector  $j$ . The total carbon emissions embodied in the final demand are:

$$E = F(I - A)^{-1}Y = FLY \tag{2}$$

where  $F$  is direct emissions intensities and  $F(I - A)^{-1}$  is emissions multipliers.

### Modified hypothetical extraction method (HEM)

The HEM aims to estimate the embodied emissions linkage by comparing emissions changes between the original economic system and the hypothetical economic system that the target sectors have been removed (He et al. 2017; Du et al. 2019). We assume that the whole economic system is decomposed into two groups, i.e.,  $S$  is the target group with a given sector or several similar sectors;  $-S$  is the remaining sectors of the economy. Here, note that in order to simplify equation, we assume the sector number of group  $S$  equals to group  $-S$ , such that  $A_{s,-s}$  and  $A_{-s,s}$  are square matrices. The total emissions can be expressed as:

$$\begin{pmatrix} E_s \\ E_{-s} \end{pmatrix} = \begin{pmatrix} F_s & 0 \\ 0 & F_{-s} \end{pmatrix} \begin{pmatrix} (I - A_{s,s})^{-1} & (I - A_{s,-s})^{-1} \\ (I - A_{-s,s})^{-1} & (I - A_{-s,-s})^{-1} \end{pmatrix} \begin{pmatrix} Y_s \\ Y_{-s} \end{pmatrix} \tag{3}$$

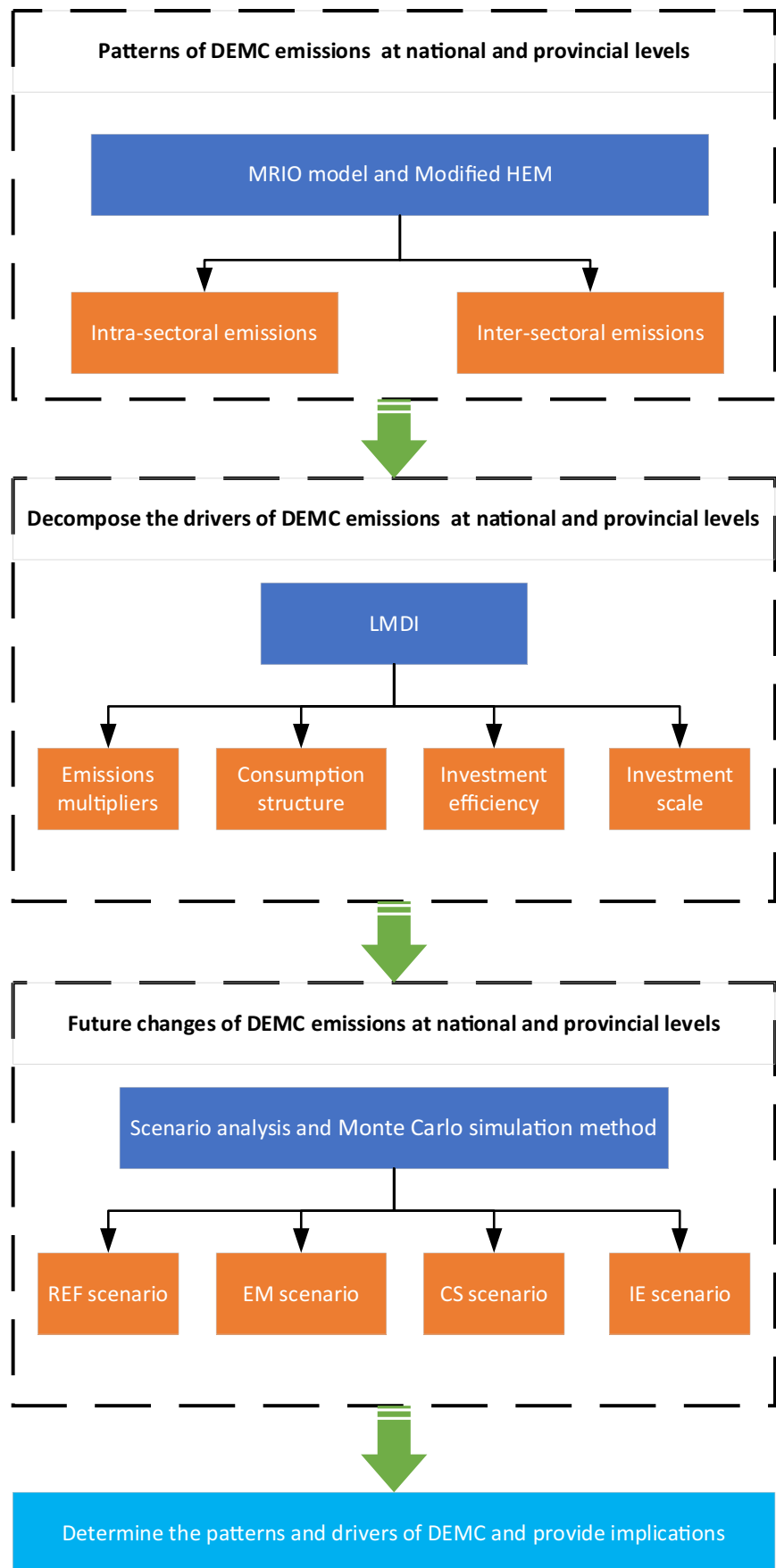
where  $E = \begin{pmatrix} E_s \\ E_{-s} \end{pmatrix}$  is the vector of total emissions;

$F = \begin{pmatrix} F_s & 0 \\ 0 & F_{-s} \end{pmatrix}$  is a diagonal matrix of emissions intensities;

$(I - A)^{-1} = \begin{pmatrix} (I - A_{s,s})^{-1} & (I - A_{s,-s})^{-1} \\ (I - A_{-s,s})^{-1} & (I - A_{-s,-s})^{-1} \end{pmatrix}$  is the Leontief

inverse matrix; and  $Y = \begin{pmatrix} Y_s \\ Y_{-s} \end{pmatrix}$  is the final demand vector.

Fig. 1 Research flow chart



Based on the HEM, the target sector does not exchange products with any sectors; thus, coefficients  $A_{s,-s}$  and  $A_{-s,s}$  are set to zeros. If there are not any hypothetical intersectoral relations between the two sector groups, the carbon emission is estimated as.

$$\begin{pmatrix} E_s \\ E_{-s} \end{pmatrix} = \begin{pmatrix} F_s & 0 \\ 0 & F_{-s} \end{pmatrix} \begin{pmatrix} (I - A_{s,s})^{-1} & 0 \\ 0 & (I - A_{-s,-s})^{-1} \end{pmatrix} \begin{pmatrix} Y_s \\ Y_{-s} \end{pmatrix} \tag{4}$$

The impact of the extracted block due to the change in production can be estimated by comparing the result with that based on the original full IO table.

Following Sajid et al. (2020), in order to estimate DEMC emissions, we assume that coefficients  $A_{s,-s}$  and  $A_{-s,s}$  are set to zeros. This means that our estimation considers the emission intensities of the entire supply chain, as  $L_{s,s}$  and  $L_{-s,s}$  represent the internal consumption and inter-sectoral consumption of target sector respectively. Moreover, since we focus on the emissions induced by the final demand of manufacturing industry, we assume that the final demand of the group  $-s$  is extracted. Therefore, the total DEMC emissions are

$$\begin{pmatrix} E_s^* \\ E_{-s}^* \end{pmatrix} = \begin{pmatrix} F_s & 0 \\ 0 & F_{-s} \end{pmatrix} \begin{pmatrix} (I - A_{s,s})^{-1} & 0 \\ 0 & (I - A_{-s,-s})^{-1} \end{pmatrix} \begin{pmatrix} Y_s \\ 0 \end{pmatrix} = \begin{pmatrix} F_s & 0 \\ 0 & F_{-s} \end{pmatrix} \begin{pmatrix} L_{s,s} & 0 \\ L_{-s,s} & 0 \end{pmatrix} \begin{pmatrix} Y_s \\ 0 \end{pmatrix} \tag{5}$$

Based on Duarte et al. (2002) and Sajid et al. (2019b), the DEMC emissions can be decomposed into two components, namely, inter-sectoral and intra-sectoral emissions as

$$DEMC = EIR + EIA = F_{-s}(L_{-s,s})Y_s + F_s(L_{s,s})Y_s = M_{-s}Y_s + M_sY_s \tag{6}$$

where  $EIR$  is the DEMC emissions of inter-sectoral consumption;  $EIA$  is the DEMC emissions of intra-sectoral consumption;  $F$  is the diagonalized matrix of emissions intensities for target and other sectors;  $L$  is the column of intermediate consumption of manufacturing sectors;  $M = FL$  is the column of the emission multipliers for target and other sectors.

### LMDI decomposition analysis

There are two well-known factor decomposition methods, namely the structural decomposition method (SDA) and the index decomposition analysis (IDA) method. Compared with SDA, the IDA has the characteristics of simplicity and flexibility, which makes it more popular among scholars (Ang and Zhang 2000; Ang 2004). Among various IDA methods, the LMDI method (Xu and Ang 2013; Ang 2015; Ang and Goh 2019), as the first choice, has been extensively applied to carbon emission issues, because of its advantages of theoretical foundation, adaptivity, easy operation, and readability. After general consideration, here we employ LMDI model. To carry out the LMDI analysis, we investigate four

drivers: emission multipliers ( $M_{ir}$ ), consumption structure ( $G_{ir}$ ), investment efficiency ( $K_r$ ), and investment scale ( $V_r$ ), as described by the equation:

$$EIR = \sum_r \sum_i M_{-s}^{ir} \frac{Y_s^{ir}}{Y_{-s}^{ir}} \frac{Y_s^r}{V_s^r} V_s^r = \sum_r \sum_i M_{-s}^{ir} G_s^{ir} K_s^r V_s^r \tag{7}$$

$$EIA = \sum_r \sum_i M_s^{ir} \frac{Y_s^{ir}}{Y_{-s}^{ir}} \frac{Y_s^r}{V_s^r} V_s^r = \sum_r \sum_i M_s^{ir} G_s^{ir} K_s^r V_s^r \tag{8}$$

Since the DEMC emissions are affected by both domestic production and non-domestic production of imported goods, referring to Yuan et al. (2019), we sum the DEMC emissions related with the upstream emissions across all source provinces to estimate the total DEMC emissions induced by sector  $i$  in province  $r$ . Then, we divide the total DEMC emissions induced by sector  $i$  in province  $r$  by the corresponding total consumption. Thus, the average emission multiplier for sector  $i$  in province  $r$  ( $\bar{M}_{ir}$ ), weighted by the consumption originating in province  $s$ , can be estimated as

$$\bar{M}_{ir} = \frac{\sum_s M_{is} Y_{isr}}{\sum_s Y_{isr}} \tag{9}$$

where  $Y_{isr}$  is the consumption of sector  $i$  in province  $r$  originating in province  $s$ , and  $M_{is}$  is the emission multiplier of sector  $i$  in province  $s$ .

After summing the consumption across the source provinces, we calculate the average consumption structure of province  $r$  as

$$\bar{G}_{ir} = \frac{\sum_s G_{isr} Y_{isr}}{\sum_s Y_{isr}} \tag{10}$$

where  $G_{isr}$  is the ratio of consumption of sector  $i$  in province  $r$  that is supplied from province  $s$  in the total consumption in province  $r$ .

Using the LMDI decomposition equations, the effects of different factors can be presented as below:

$$\begin{aligned} \Delta EIR = EIR^t - EIR^0 &= \Delta E_{-s}^M + \Delta E_s^G + \Delta E_s^K + \Delta E_s^V = L(EIR^t, EIR^0) \ln \left( \frac{\bar{M}_{-s}^{irt}}{\bar{M}_{-s}^{i0r}} \right) \\ &+ L(EIR^t, EIR^0) \ln \left( \frac{\bar{G}_s^{irt}}{\bar{G}_s^{i0r}} \right) + L(EIR^t, EIR^0) \ln \left( \frac{K_s^{rt}}{K_s^{r0}} \right) + L(EIR^t, EIR^0) \ln \left( \frac{V_s^{rt}}{V_s^{r0}} \right) \end{aligned} \tag{11}$$

$$\begin{aligned} \Delta EIA = EIA^t - EIA^0 &= \Delta E_s^M + \Delta E_s^G + \Delta E_s^K + \Delta E_s^V = L(EIA^t, EIA^0) \ln \left( \frac{\bar{M}_s^{irt}}{\bar{M}_s^{i0r}} \right) \\ &+ L(EIA^t, EIA^0) \ln \left( \frac{\bar{G}_s^{irt}}{\bar{G}_s^{i0r}} \right) + L(EIA^t, EIA^0) \ln \left( \frac{K_s^{rt}}{K_s^{r0}} \right) \\ &+ L(EIA^t, EIA^0) \ln \left( \frac{V_s^{rt}}{V_s^{r0}} \right) \end{aligned} \tag{12}$$



where  $L(EIR^t, EIR^0) = \frac{EIR^t - EIR^0}{\ln EIR^t - \ln EIR^0}$  and  $(EIA^t, EIA^0) = \frac{EIA^t - EIA^0}{\ln EIA^t - \ln EIA^0}$ .

Therefore, the changes in DEMC emissions in years  $t$  and  $0$  can be decomposed as follows:

$$\Delta DEMC = \Delta E^M + \Delta E^G + \Delta E^K + \Delta E^V \quad (13)$$

## Scenario design

In the scenario design, we provide a reference scenario (Scenario REF) and three green development scenarios, namely Scenario Emission Multiplier (Scenario EM), Scenario Consumption Structure (Scenario CS), and Scenario Investment Efficiency (Scenario IE). In the Scenario REF, future investment scale is based on China's current investment growth speed, and no additional emission mitigation actions will be implemented. In the three green development scenarios, to analyze the effectiveness of different emission reduction measures, the investment scale of manufacturing industry is the same with the Scenario REF, while different emission reduction measures are gradually added in different scenarios. In the Scenario EM, the emission multipliers are expected to decrease considering China's peak emission target. In the Scenario CS, Chinese structure adjustment policies led to an increase in the consumption share of knowledge-intensive manufacturing industry. The Scenario IE hopes that the investment efficiency will decrease. Thus, in the Scenario IE, all factors are adjusted referring to policy targets.

As the scenarios analysis is not a dynamic projection that neglects the future volatility, we combine the Monte Carlo simulation method with scenario design to estimate future DEMC emissions. Thus, the possible intervals of projected emissions can be obtained according to the uncertainties of factors. Since the expected value and the change range of factors can be pre-estimated referring to previous literatures (Zhang et al. 2021, 2020b; Lin and Liu 2010), we first define prior distribution for future growth rates of factors as the triangular distribution. This is because the triangular distribution approximates a lognormal distribution, which is available for a description of many natural phenomena. It is usually used for when you have no idea what the distribution is but you have a good guess for the minimum value, the maximum value, and the expect value for variables. Then, we randomly draw samples such that repeated simulations are developed based on the prior distribution. Finally, we present the projected results according to the probability distribution diagrams. We conducted 100,000 Monte Carlo simulations. The details of scenarios setting are presented below.

a. **Scenario REF.** The Scenario REF was considered as a baseline scenario. The manufacturing investment scale is based on China's FYPs with emission multipliers,

consumption structure and investment efficiency held constant at the 2017 level. This means that no additional emission mitigation actions will be taken. We use a sample of 30 provinces between 2007 and 2017 and observe that the investment scale in manufacturing industry is strongly correlated with total fixed asset investment (Fig. S1). Thus, we estimate the elasticities of investment scale based on the function of total fixed asset investment in 30 provinces (Fig. S2). Then, we assumed that a 1% increase of total fixed asset investment would lead to a specific percentage increase of the investment in manufacturing industry. This means that the annual average growth rates (AAGRs) of provincial manufacturing investment scale are based on the AAGRs of provincial total fixed asset investment. The AAGRs of total fixed asset investment in 30 provinces are from Zhang et al. (2020b). The AAGRs of provincial manufacturing investment during 2018–2019 are from the Provincial Statistical Yearbook. Considering the uncertainties of policy implementations, the Best level and Baseline level are based on the Middle level of AAGRs. According to Lin and Liu (2010), we assume the Best level and Baseline level for the AAGRs of investment scale vary with 1% fluctuation of the Middle level. The detailed assumptions of the AAGRs of provincial investment scale over 2020–2035 in the Scenario REF are given in Tables S1.

b. **Scenario EM.** In the Scenario EM, the investment scale of manufacturing industry is the same with that in the Scenario REF, and consumption structure and investment efficiency are based on those of 2017. However, the emissions multipliers are expected to decrease. According to Eq. (6), the emission multipliers are dominated by direct emissions intensity ( $F$ ) and the intermediate consumption matrix ( $L$ ). We could not consider the change of the  $L$  in the scenario since specific policy target could not be provided as the reference of the improvement of linkage across sectors. However, the 14th Five-Year Plan proposed that the emissions per unit of GDP would decline by 18% from 2021 to 2025. China's Intended Nationally Determined Contributions (INDC) set the goal to reduce CO<sub>2</sub> emissions per unit of GDP by 60–65% compared to the 2005 level. Thus, we assume that the intermediate consumption coefficient matrix is constant, and the emissions multipliers would continuously decline. However, the decline rates of the emissions multipliers may gradually reduce due to the increase in the marginal costs and technical difficulties. Thus, in this scenario, we used 2017, the last year of the sample period, as the base year for emissions multipliers. We assume the decline rates of emissions multipliers during 2018–2020 and 2021–2025 conform to the 13<sup>th</sup> and 14<sup>th</sup> FYPs target. Moreover, considering the target

of emissions peaking, for other periods of time, we used 90% and 80% of the AAGR in 2021–2025 to obtain the decline floor of the emissions multipliers. Considering the uncertainties of policy implementations, referring to Lin and Liu (2010), the Best level and Baseline levels are 2% fluctuation for the AAGRs of emissions intensity based on the Middle level. The detailed data are listed in the Table S2.

- c. **Scenario CS.** In the Scenario CS, the investment scale and emissions multipliers of manufacturing industry are based on the projection of the Scenario EM, and there are no advancements in investment efficiency since 2017. Based on the manufacturing development setting from “Made in China 2025,” there are changes in the consumption distribution among different manufacturing industries. Moreover, with the manufacturing industry entering a period of restructuring and transformation, China issued its 14<sup>th</sup> FYPs to develop high-end manufacturing. These provide opportunities for the development of knowledge-manufacturing industry. We divide 16 manufacturing sectors into 3 categories, namely labor-manufacturing industry, capital-manufacturing industry, and knowledge-manufacturing industry (Table S3). During 13<sup>th</sup> FYP, the consumption share of knowledge-intensive manufacturing industry in China increased with a 6% AAGR. We assume that the share of knowledge-intensive manufacturing industry will keep the same speed with a 6% AAGR during 2018–2025. The AAGR for the consumption share of knowledge-intensive manufacturing during 2026–2030 and 2031–2035 will be 1.0 and 2.0% higher than that during 2018–2025 respectively. Moreover, a proportional increase in knowledge-intensive manufacturing industry was achieved at the expense of decreases in the labor-manufacturing and capital-manufacturing industries. Thus, the Scenario CS represents a series of possible situational changes in the shares of the other two manufacturing industries. Mathematically, the share of a labor/capital intensive sector  $i$  in the total consumption of labor- and capital-intensive industries in province  $r$  in 2017 is  $S_{ir}^{2017}$ . We assume that with the increase in the consumption share of the knowledge-intensive industry, the share of labor- and capital-intensive industries in the total demand of manufacturing industry in province  $r$  in the Scenario CS is  $S_r^*$ . The share of a labor/capital intensive sector  $i$  in the total demand of manufacturing industry in province  $r$  in the Scenario CS ( $S_{ir}^*$ ) can be estimated as

$$S_{ir}^* = S_r^* * S_{ir}^{2017}. \quad (14)$$

According to Lin and Liu (2010), we assume that the share of knowledge-intensive manufacturing industry

increases with a 1% AAGR at the Baseline level and a 3% AAGR at the Best level.

- d. **Scenario IE.** In the Scenario IE, we assume the investment scale, emissions multipliers, and consumption structure remained the same as the Scenario CS, while the investment efficiencies in China’s 30 provinces are expected to be lower than those in the Scenario CS. This is because the Chinese government has noticed the serious overcapacity problem and taken measures to eliminate outdated production capacity and decrease the investment efficiency. Combined with the studies on the investment efficiency (Zhang et al. 2021), we assume that the provincial investment efficiency during 2018–2020 in this scenario will be 2% lower than that in the Scenario REF. For other periods of time, the AAGRs of investment efficiency are adjusted according to the historical data of each province. According to Lin and Liu (2010), the assumption process of Best level and Baseline level of the AAGRs of the investment efficiency is the same with the AAGRs of investment scale in Scenario REF.

## Data sources

The China’s multi-regional input–output tables (MRIO) data for 2007 and 2010 are from Liu et al. (2012) and Liu et al. (2014), respectively. The MRIO tables for 2012, 2015, and 2017 are from CEADs database (<https://ceads.net/>). The China’s MRIO tables for 2007 and 2010 include 30 provinces excluding Tibet, while the MRIO tables for 2015 and 2017 include 31 provinces. Since the carbon emissions in Tibet are small, only accounting for smaller than 1% of the total national emissions, we only consider 30 provinces’ data. We use economic data in the constant price (base year: 2007), and the price index data are from China Price Statistical Yearbook. The emissions data (which include process-emissions) are from CEADs database. The investment scale data are from Statistical Yearbook of the Chinese Investment in Fixed Assets. Regarding the data for scenarios analysis, we project AAGRs of four factors from 2020 to 2035 according to the related policies (details can be seen in Table S5).

## Results

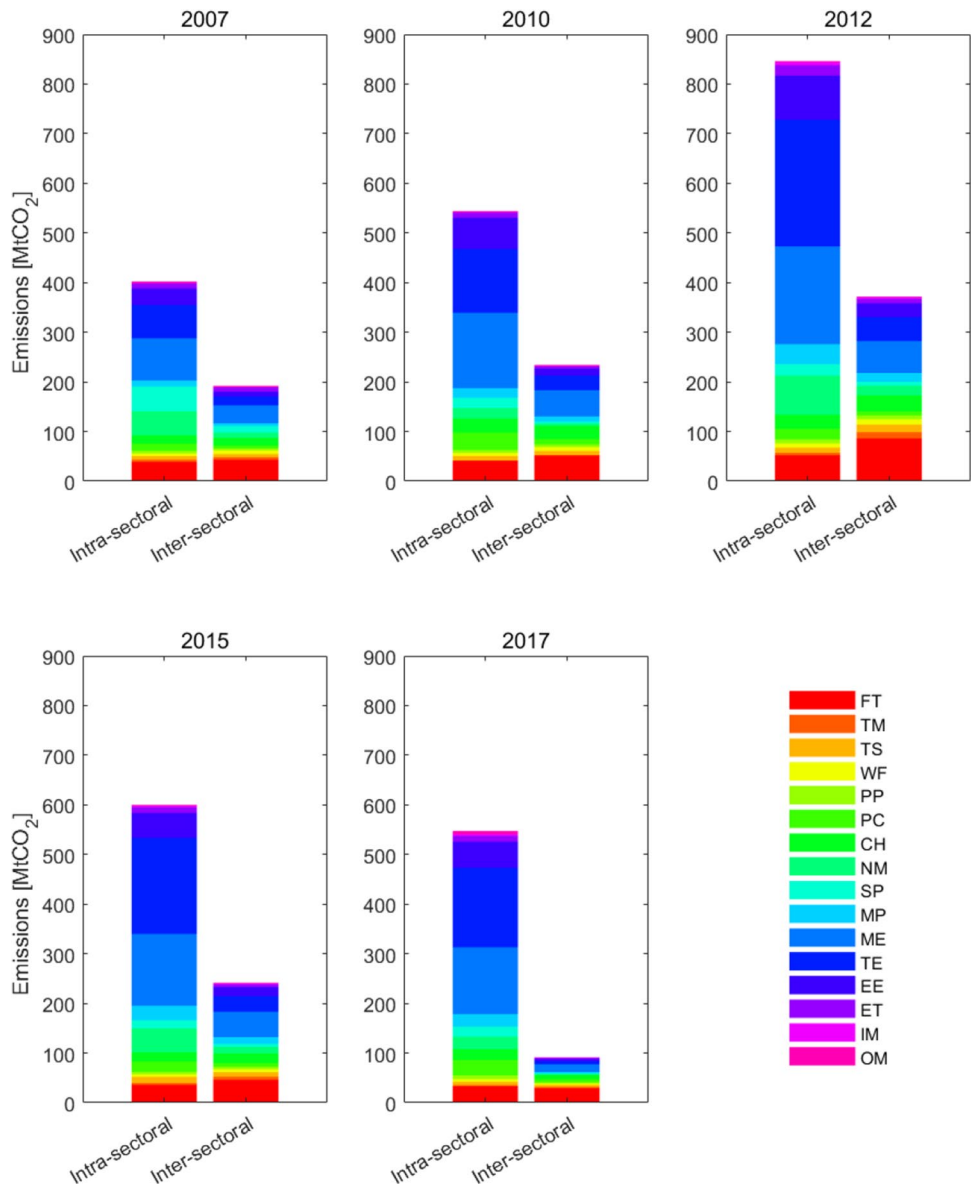
### Estimation of DEMC emissions

China’s DEMC emissions from the intra-sectoral consumption were higher than those from inter-sectoral consumption (Fig. 2). During 2007–2012, the intra-sectoral emissions increased from 402 to 846 Mt. The highest amount of intra-sectoral emissions at 85 Mt came from

ME (the sectoral details can be seen Table S3) in 2007 and the largest amount of intra-sectoral emissions in 2012 at 255 Mt from TE. During 2012–2017, the intra-sectoral emissions saw a decrease of –298 Mt. In 2017, the TE sector was still the largest factor affecting these emissions, but its intra-sectoral emissions decreased to 160 Mt. During 2007–2012, as emissions linkage experienced increase due to large-scale sectoral trade, the inter-sectoral emissions increased from 192 to 372 Mt. The labor manufacturing industry was the most significant source that drove the inter-sectoral emissions. For example, FT, with an average of 60 Mt, had the largest inter-sectoral emissions. The inter-sectoral emissions also saw the most dramatic decrease during 2012–2017, from 371 to 91 Mt. The FT was still mainly responsible for the inter-sectoral

emissions, but its emissions decreased to 29 Mt in 2017. This indicates that labor manufacturing industry generated large emissions primarily in the production of supplying products for downstream sectors. Shandong with an average of 78 Mt during 2007–2015 was the largest source of the intra-sectoral emissions, which was mainly from the ME sector with an average of 25 Mt (Fig. S3). In 2017, the intra-sectoral emissions from Shandong decreased to 55 Mt and Hebei became the largest source of the intra-sectoral emissions with 67 Mt. During 2007–2015, the largest source of inter-sectoral emissions was again Shandong (an average of 24 Mt), which was mainly from FT with an average of 6 Mt. Zhejiang (9 Mt) was the largest source of the inter-sectoral emissions in 2017, and the FT (2 Mt) was its key factor.

**Fig. 2** DEMC emissions from the inter-sectoral consumption and intra-sectoral consumption. Note: the abbreviation of sectors is shown in the Table S3





## Decomposition analysis of DEMC emissions

During the period of 2007–2015, the investment scale had the largest positive impact on the DEMC emissions (Fig. 3). The gross investment increased by double during 2007–2010, contributing to a 22.8% year<sup>-1</sup> and 22.3% year<sup>-1</sup> increase of intra- and inter-sectoral emissions respectively. During 2010–2015, the AAGR of investment scale slowed down gradually, decreasing to +19.7% year<sup>-1</sup> and +20.0% year<sup>-1</sup> during 2010–2012, then to +10.6% year<sup>-1</sup> and +10.1% year<sup>-1</sup> during 2012–2015. However, the investment scale was still the key driver of the increase of DEMC emissions during the two periods. This is because the impacts of investment scale on the DEMC emissions from ME and TE were significant. For example, the investment scale induced the intra-sectoral emissions of TE increase significantly by 78 Mt during 2012–2015 (Fig. S4). The investment scale had a small negative impact on the DEMC emissions during 2015–2017, decreasing with -0.4% year<sup>-1</sup> and -0.5% year<sup>-1</sup> of intra- and inter-sectoral emissions respectively. During the three periods of 2007–2010, 2012–2015, and 2015–2017, the emission multipliers were the most critical inhibiting factors on the DEMC emissions. For example, during 2015–2017, the emissions multipliers contributed to a -4.1% year<sup>-1</sup> and -40.3% year<sup>-1</sup> decrease of intra- and inter-sectoral emissions respectively. However, during 2010–2012, the emission multipliers had a positive contribution to inter-sectoral emissions increase with +4.5% year<sup>-1</sup>. This was mainly from the positive impact of emissions multipliers on the inter-sectoral emissions in FT and CH, which induced a 14 and 9 Mt increase of emissions (Fig. S4). During 2007–2010 and 2012–2015, the investment efficiency reduction had positive impacts on DEMC emissions reduction. For example, the investment efficiency reduction contributed a -14.9% year<sup>-1</sup> reduction of intra-sectoral emissions during 2012–2015. The important contribution was mainly from the TE, in which the investment efficiency reduction contributed a -108 Mt and -18 Mt reduction of intra-sectoral and inter-sectoral emissions respectively. During 2010–2012 and 2015–2017, the investment efficiency improvement had a small contribution to the DEMC emissions increase. For example, the investment efficiency improvement resulted in intra-sectoral emissions increase slightly by +4.0% year<sup>-1</sup> during 2015–2017. The impact of consumption structure on the intra-sectoral emission during 2010–2012 and the inter-sectoral emissions during 2007–2010 was positive. For example, the changes of consumption structure led to intra-sectoral emissions increase slightly by +4.0% year<sup>-1</sup> during 2010–2012. This was mainly from the increase in the consumption share of capital-intensive manufacturing industry (e.g., NM and TE, Fig. S4). However, with the

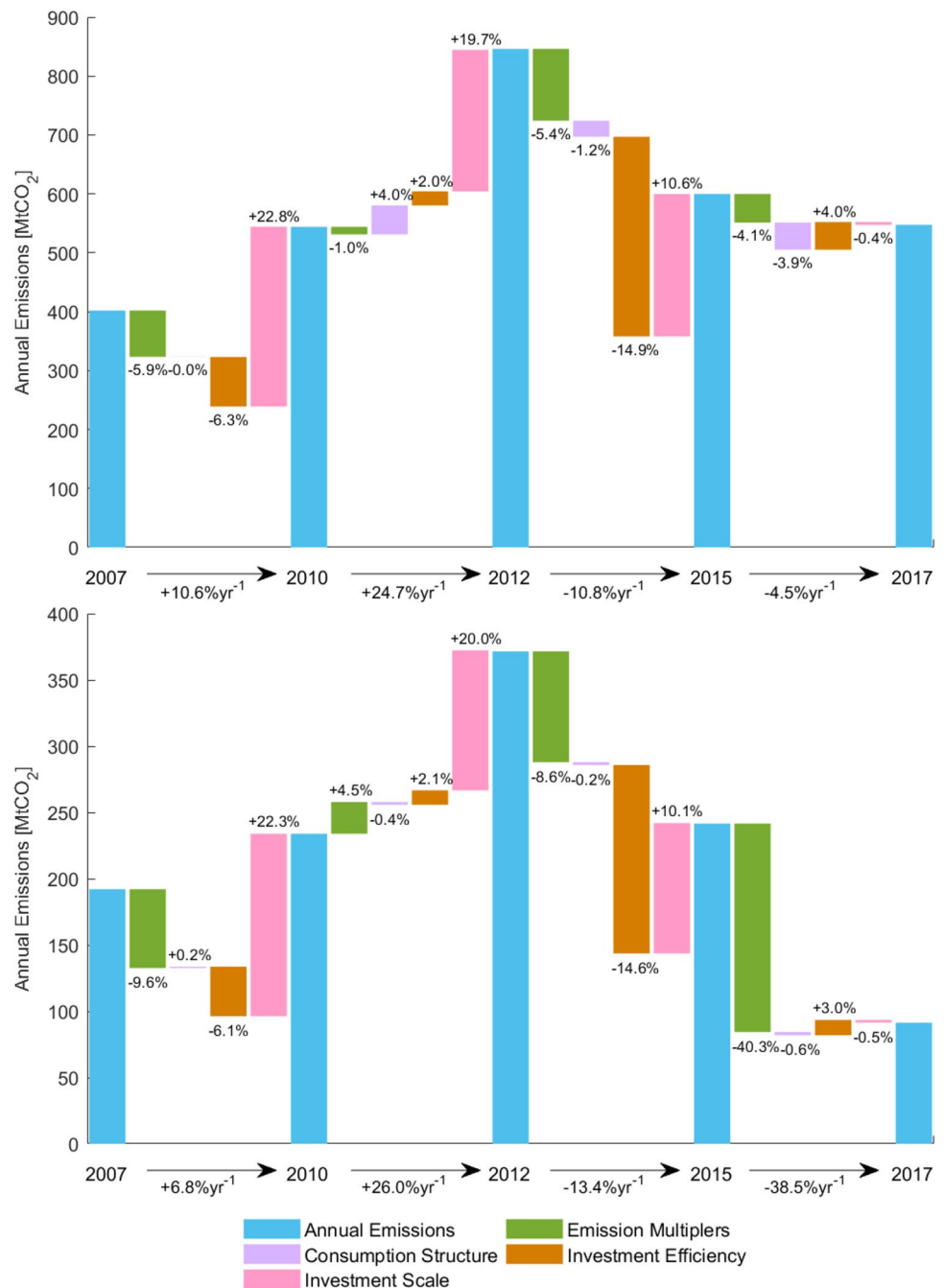
consumption structure transformation towards knowledge-intensive manufacturing industry, the consumption structure had negative effects on the DEMC emissions during 2012–2017. For example, the consumption structure induced a 3.9% year<sup>-1</sup> decrease of intra-sectoral emissions decrease during 2015–2017.

The investment in manufacturing industry increased quickly in most Chinese provinces during 2007–2015, especially several developing industrial provinces (e.g., Shandong and Hebei) actively develop their energy-intensive industries, causing mass investment in manufacturing industry (Fig. 4). During 2015–2017, with the shift of economic structure from investment-led to consumption-driven, the investment scale had a negative effect on the DEMC emissions in 13 provinces, including several key industrial provinces (e.g., Tianjin, Hebei, Shanxi, Liaoning, Jilin). The investment scale had the largest negative impact on the DEMC emissions in Liaoning, inducing intra-sectoral and inter-sectoral emissions of Liaoning decrease significantly by -30 Mt and -7 Mt during 2015–2017. This negative impact was mainly associated with the ME sector (-14 Mt, Fig. S5). During 2007–2017, the emission multipliers prevented the increase of inter-sectoral emissions in most of provinces. However, during 2010–2017, the emissions multipliers had the largest positive emissions effect on intra-sectoral emissions in several developing industrial provinces (e.g., Hebei, Inner Mongolia, and Shandong), which was mainly from the capital-intensive industry (e.g., ME in Hebei and CH in Inner Mongolia during 2010–2012, Fig. S6). The investment efficiency had the largest negative impact on the DEMC emissions in Shandong during 2012–2015, which induced intra- and sectoral emissions decrease significantly by -44 Mt and -17 Mt respectively. This was mainly from the decrease of investment efficiency in ME and TE, which contributed to a -18 Mt and -19 Mt decrease of emissions respectively. Moreover, the investment efficiency had the largest positive effect on the DEMC emissions in Liaoning during 2015–2017, leading to intra- and sectoral emissions increase significantly by 25 Mt and 7 Mt respectively. This was mainly from the increase of investment efficiency in ME, which led to a 13 Mt increase of emissions (Fig. S7). Consumption structure had a limited impact on the DEMC emissions across all provinces. Its largest negative impact was from Henan during 2015–2017, leading to a -7 Mt decrease of intra-sectoral emissions. This was because that the consumption share of TE in Henan decreased, which induced a -10 Mt decrease of emissions (Fig. S8).

## Mitigation potential of DEMC emissions

We use the Monte Carlo simulation to project China's DEMC emissions under four scenarios. To remove possible extreme values, we present projection results using

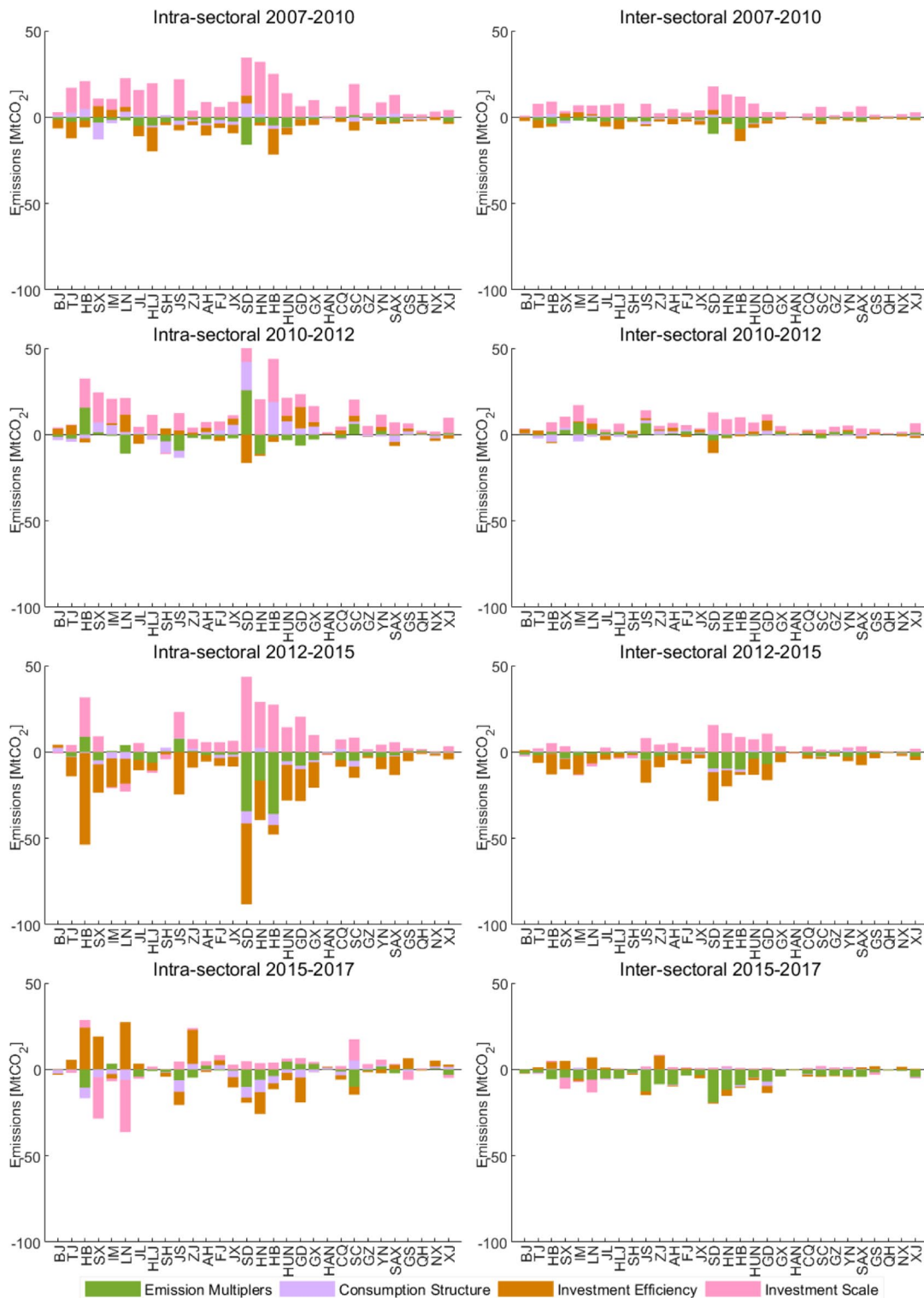
**Fig. 3** Aggregated impact of driving factors on (a) intra-sectoral emissions and (b) inter-sectoral emissions. Note: as the number of years is not the same in both periods, we display compound annual growth or reduction. The compound annual rate of total emissions ( $r$ ) is related to the total rate ( $R$ ) across  $n$  years as  $r = \sqrt[n]{1 + R} - 1$ , 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



95% confidence intervals. Moreover, the factors of investment scale and efficiency during 2018–2019 are based on historical data; thus, we only present projected results for the period of 2020–2035. Under the Scenario REF, we assume that China's investment scale of manufacturing industry will maintain increasing although the AAGR will gradually decrease during 2020–2035. Since a sustained investment growth will be supported by massive production of manufacturing industry, China's DEMC emissions will continue to increase before 2035, from 776–789 Mt in 2017 to 2300–2574 Mt in 2035 (Fig. S9). Moreover, only

Shanghai is likely to peak its DEMC before 2030 (Fig. 6 and Fig. S10).

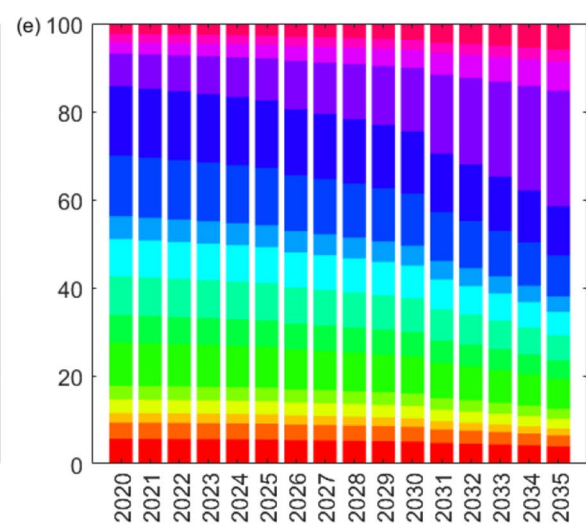
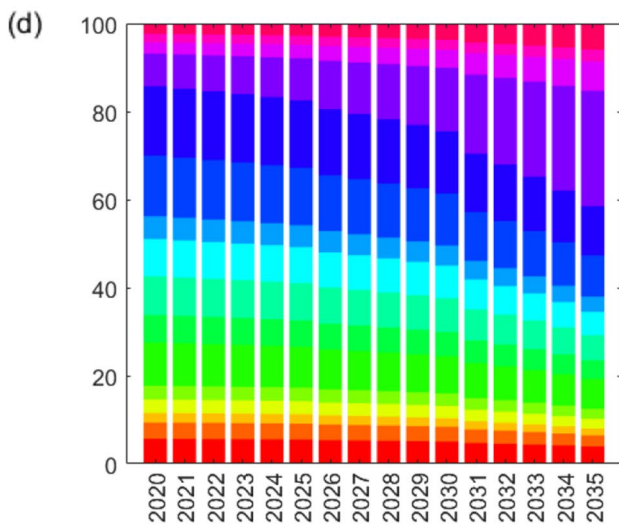
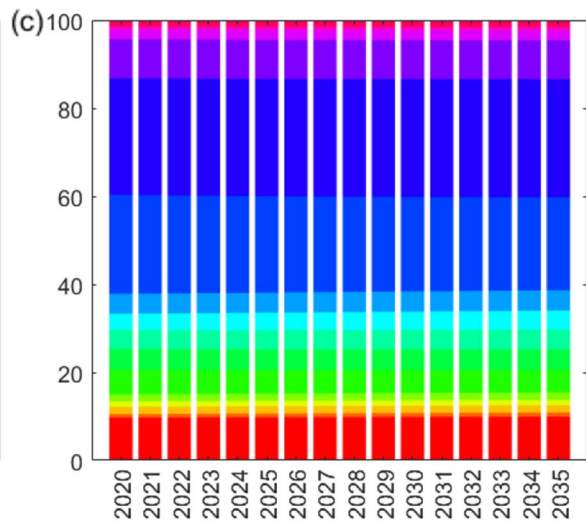
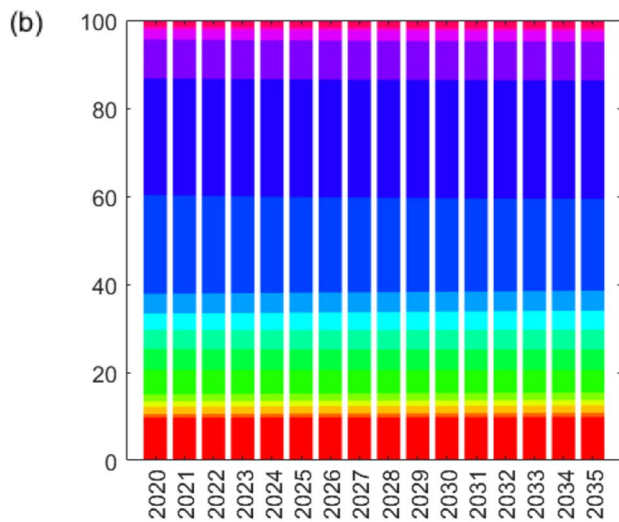
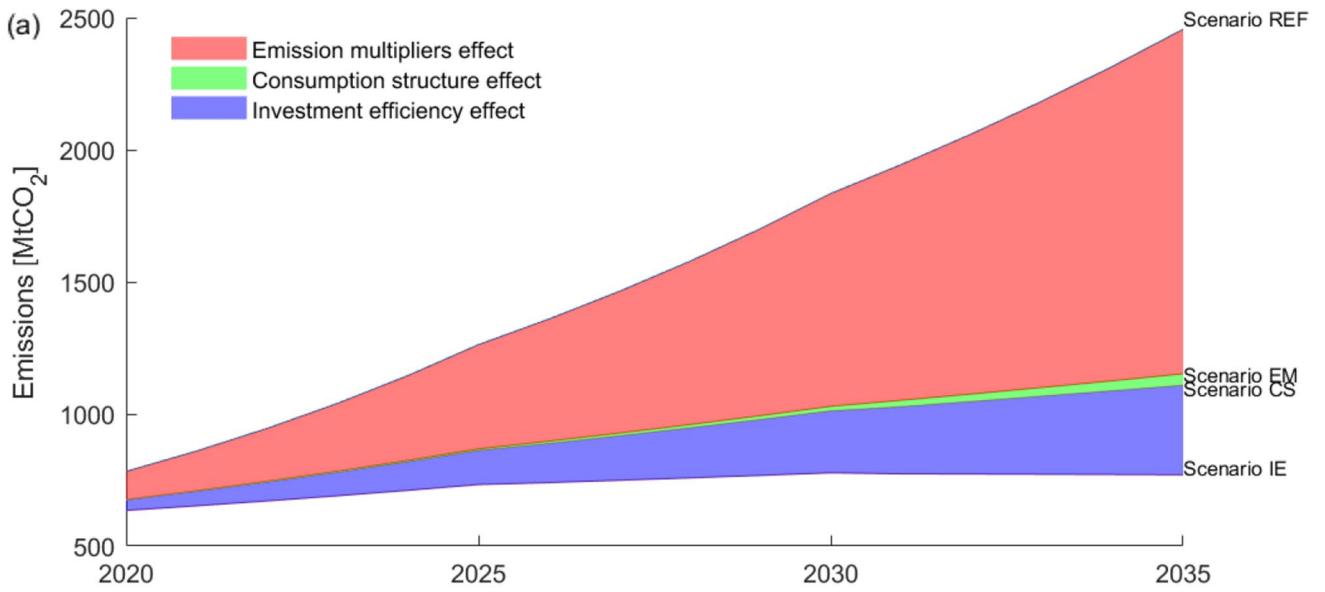
Under the Scenario EM, China's DEMC emissions will increase relatively slower, reaching 1091–1211 Mt in 2035. The emissions multipliers show great potential in carbon mitigation, leading to a 53.1% emissions reduction compared with the Scenario REF in 2035 (based on median value of projection, Fig. 5a). However, the peaking of DEMC emissions will not be reached before 2030 under this scenario. Impacted by the mitigation effect of emission multipliers, only five provinces (including Beijing, Liaoning,



**Fig. 4** Contributions of driving factors to DEMC emissions changes in 30 provinces. Note: the provincial details can be seen Table S4

Heilongjiang, Shanghai, and Hainan) remain the persistent reduction, and two provinces (i.e., Shanxi and Xinjiang) are likely to peak emissions prior to 2030 (Fig. 6 and Fig. S11). This indicates that although the reduction of emission

multipliers has the largest emission mitigation effect among the three measures (EM, CS, and IE), China’s current carbon intensity target is not enough for realizing the 2030 emission peak target in terms of DEMC emissions.

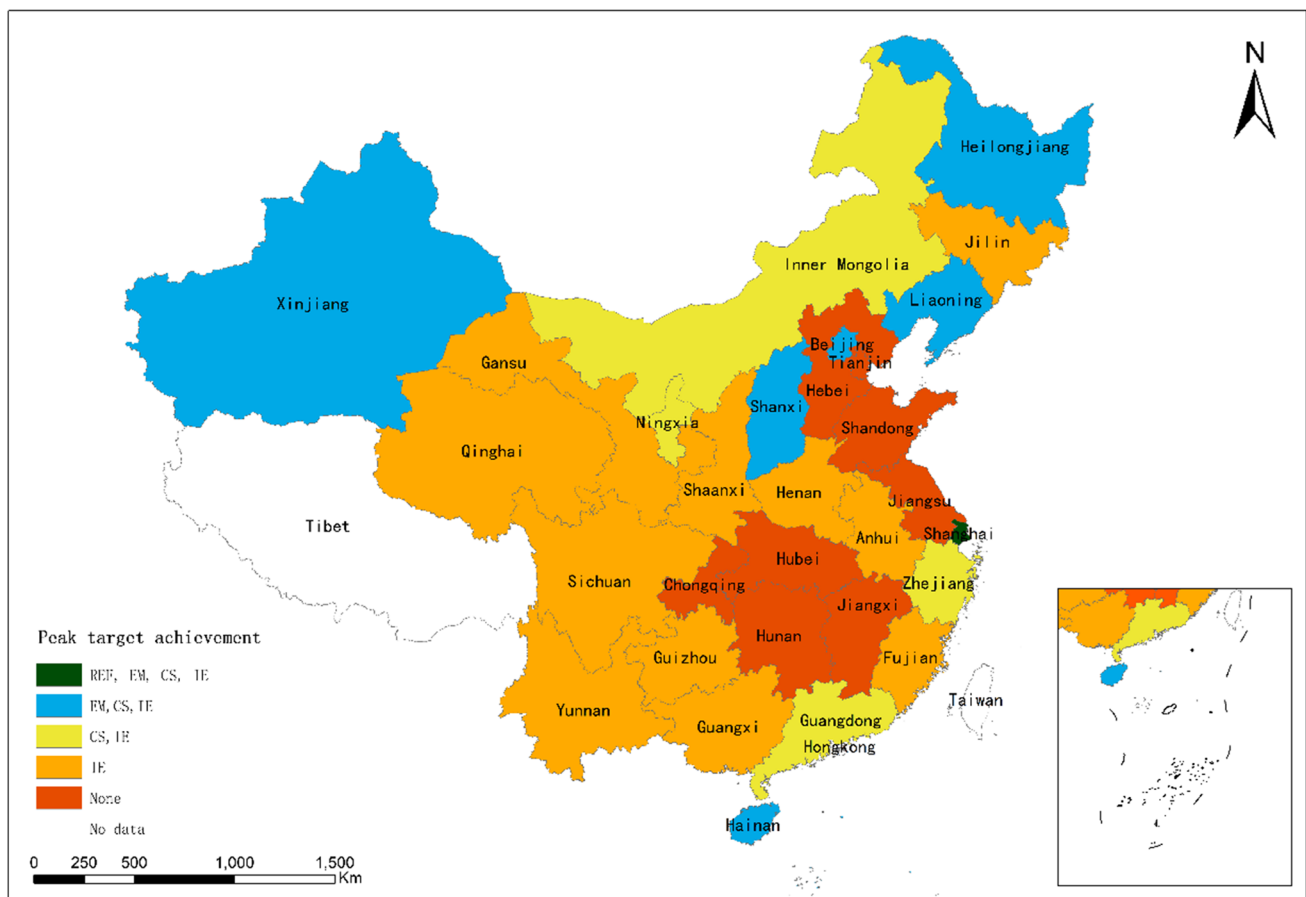


**Fig. 5** Results of scenario analysis. **a.** Mitigation potential of China’s DEMC emissions. Note: the results here are based on median value of projection. **b.** Emissions share changes of manufacturing sectors in the Scenario REF. **c.** Emissions share changes of manufacturing sectors in the Scenario EM. **d.** Emissions share changes of manufacturing sectors in the Scenario CS. **e.** Emissions share changes of manufacturing sectors in the Scenario IE

In the Scenario CS, the measure of consumption structure transformation can bring about a avoidance of emissions of 243 Mt, such that the DEMC emissions will drop to 1043–1173 Mt in 2035 (Fig. 5a and Fig. S9). The main reason is that in this scenario, the consumption shares of labor and capital industries, which are important sources of DEMC emissions, will reduce. However, the goal of carbon peaking by 2030 is still difficult to achieve in the Scenario CS. This reveals that China’s existing polices for manufacturing structure shift cannot ensure the achievement of peak target for DEMC emissions. Moreover, with the consumption structure shift, Inner Mongolia, Zhejiang, and Guangdong would peak emissions before 2030 (Fig. 6 and Fig. S12). This reflects policies that combine emission

intensities reduction and consumption structure update will have an important impact on the realization of carbon peak target in these provinces.

Under the Scenario IE, China’s DEMC first increases before 2030 and then significantly decreases after 2030. Consequently, the DEMC emissions will reach the peak at around 777 Mt in 2030 under this scenario (Fig. S9). This is because the reduction of investment efficiency significantly reduces emissions, showing greater potential in emissions reduction than the consumption structure adjustment. This implies that the reductions of investment efficiency and emission multipliers should be the priority for current policies. We can find that with fast growth of investment, following current policies and targets, none of the three single measures can realize the peaking goal by 2030. An integrated measure combining the three approaches will strengthen the control of DEMC emissions. We also find that 8 provinces (including Tianjin, Hebei, Jiangsu, Jiangxi, Shandong, Hubei, Hunan, and Chongqing) are unlikely to peak emissions before 2035 (Fig. 6 and Fig. S13). This means that further mitigation policies should be implemented in these provinces, such that more clean energy



**Fig. 6** Realization of carbon emissions peak target in China’s 30 provinces under four scenarios



technologies and environmental-friendly consumption patterns can be utilized.

Moreover, although the reduction of emissions multipliers and investment efficiency have greater reduction potential than consumption structure shift, they will have limited impact on the emissions distribution among manufacturing sectors (Fig. 5b–e). Under the Scenarios of REF and EM, labor-intensive and capital-intensive industries are the main emissions source. For example, under the Scenario REF, FT, ME, and TE account for 9.9%, 20.1%, 26.9% of the total DEMC emissions in 2035 respectively. Under the Scenario EM, the emissions share of ME in 2035 increases to 21.1%, while the emissions shares of other two sectors remain unchanged. With the consumption structure shift towards knowledge-intensive industry, the emissions shares of FT, ME, and TE in 2035 decrease to 3.9%, 11.2%, and 26.2% respectively. However, the emissions share of knowledge-intensive industry in 2035 increases from 13.4% under the Scenario EM to 41.5% under the Scenario CS. Especially, the emissions share of EE increases significantly, from 8.8% under the Scenario EM to 26.2% under the Scenario CS.

## Discussion

### Comparison with previous studies

We find that investment scale had the largest positive effect on the DEMC emissions during 2007–2015, especially in several developing provinces. These results are similar with the results of previous studies (Zhao et al. 2016; Zhang et al. 2020c; Wang et al. 2021b; Li et al. 2021). Also, we find that the investment scale had a small negative effect on the DEMC emissions during 2015–2017; this is because the new economic development model in China during recent years emphasizes to shift the balance of economic growth away from investment and toward domestic consumption (CCCEP 2015). This result is similar with other studies under China's "New Normal" period (Zheng et al. 2019; Liu et al. 2020).

Many studies indicated that the changes of emissions intensities had negative effects on the emissions (Ren et al. 2014; Liu et al. 2021; Wang et al. 2022a, b). However, our results indicate that during 2010–2012, the changes of emissions multipliers had positive impacts on the inter-sectoral emissions. This is because the emissions intensities of non-manufacturing industries did not reduce with the technological advancement when the manufacturing industry requires many non-manufacturing products to meet its own production requirements. Moreover, we find that the increase in the inter-sectoral emissions during 2010–2012 mainly comes from capital-intensive sectors (e.g., FT and CH). Therefore, decarbonizing the supply chain of capital-intensive industry by green design may be an effective way of reducing

manufacturing emissions. Several studies showed that the structural shift had a negative effect on Chinese manufacturing emissions from the perspective of production structure (Liu et al. 2015; Mi et al. 2015; Su et al. 2021). From consumption structure perspective, our results further prove that the structure transformation from labor/capital-intensive manufacturing towards knowledge-intensive manufacturing led to decreased emissions during 2012–2017.

### Policy implications

Given the investment scale expansion will drive DEMC emissions increase in the Scenario REF, China should decouple investment growth from DEMC emissions as soon as possible. The policy makers can adjust China's fixed asset investment structure, aiming to encourage a rapid development of service and high-tech industries, such that the inefficient investment of energy-intensive manufacturing industry can be avoided. As developing provinces have large investment scale effects, it is recommended that their investment should gradually shift from the manufacturing industry to service and high value-added industries.

Moreover, the scenario analysis confirms that effective consumption structure change could positively impact DEMC emissions reduction. The knowledge-intensive manufacturing industry has advantages over labor/capital-intensive manufacturing industry in emissions mitigation. Thus, we recommend that the knowledge-intensive manufacturing industry should be promoted to enable larger emission reduction arising from structure optimization. Additionally, with the consumption structure shift, we hope that the focus of emissions mitigation policy should be dynamically adjusted over time. This means that with the industry update, relevant mitigation policies should pay more attention to the energy consumption of knowledge-intensive manufacturing industry rather than labor/capital-intensive manufacturing industry.

Finally, according to the Scenario REF, China's DEMC emissions will continue to increase with the current investment development pathway. Although the Scenarios EM and CS slow down emission increases, realizing the peak of DEMC emissions in China is not possible. China's DEMC can peak before 2030 in the Scenario IE alone. Therefore, following current policy designs, the impact of any single measures on reducing DEMC emissions is not sufficient. It is necessary to integrate various mitigation measures. However, there are still 8 provinces whose DEMC emissions cannot reach peak before 2030 under the Scenario IE. This means that mitigation measures mentioned here might be not enough for realizing emissions mitigation target across all provinces. Thus, the local governments in the 8 provinces should actively seek more mitigation pathways (e.g., increase research and development input).

## Limitations

The uncertainties of our study are mainly from data and methods. Because of multiple data sources for MRIO tables, there may be problems with the consistency of the data. Moreover, we predict the provincial investment scale of the manufacturing industry according to the AAGR of total fixed investment assets. In fact, more socio-economic driving factors might explain the change of investment in manufacturing industry. Finally, constraints derived from provincial development plans and previous studies can increase the uncertainties in scenario analysis. For example, we could not consider the future change of the intermediate consumption coefficient matrix ( $L$ ) in the scenario, as specific policy target could not be provided as the reference of the improvement of linkage across sectors.

## Conclusions

Here, we defined the DEMC emissions as the emissions from the intermediate manufacturing consumption which are embedded into final demand categories. Then, we analyzed the linkage effect of DEMC emissions using the MRIO model and modified HEM method. Next, we used the LMDI analysis to identify the driving factors of DEMC emissions. Finally, we constructed scenarios to analyze the mitigation potential of DEMC at the national and provincial levels.

We found that China's DEMC emissions from the intra-sectoral consumption were higher than those from inter-sectoral consumption during 2007–2017. The main source of intra-sectoral emissions was capital-intensive manufacturing industry (e.g., ME and TE), while labor-intensive manufacturing industry (e.g., FT) was the main driver of inter-sectoral emissions. Based on factor analysis, we found that investment scale had the largest positive impact on the DEMC emissions during 2007–2015, especially in the developing provinces. However, it led to a reduction of DEMC emissions during 2015–2017 with the slowdown of investment in the new normal period. The decrease of emissions multipliers and investment efficiency had the negative impacts on the DEMC emissions. However, the emission multipliers had a positive contribution to inter-sectoral emissions increase during 2010–2012. During 2012–2017, the consumption structure change had a negative impact on the DEMC emissions. The scenario analysis shows that in the Scenario REF, China's DEMC emissions will continue to increase with the current investment development pathway. Although technological improvement and consumption structure shift in the Scenarios EM and CS lead to a relatively slower emission growth, achieving the peak of DEMC emissions in China is not possible. Only the Scenario IE that integrates all the three mitigation measures can help

China peak its DEMC emissions in 2030. However, there are still 8 provinces whose DEMC emissions are unlikely to peak before 2030. Thus, we advised to control the high expansion rate of investment in manufacturing industry, particularly in developing provinces. The developing industrial provinces should focus on the technological improvement in the supply chain of manufacturing industry. Moreover, the transformation of consumption structure should be encouraged to avoid over production capacity in the labor/capital intensive industries.

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**Author contribution** All authors contributed to the study conception and design. Specific contributions for each author are below.

RY: conceptualization, data curation, formal analysis, methodology, software, investigation, writing—original draft.

HL: conceptualization, methodology, writing—review, editing, supervision.

YG: data curation, methodology.

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**Data availability** 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.

## Declarations

**Ethics approval** Not applicable.

**Consent to participate** Not applicable.

**Consent for publication** Not applicable.

**Competing interests** The authors declare no competing interests.

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