Journal of Industrial Ecology (2026) 30:1147–1160
https://doi.org/10.1007/s44498-026-00078-0

RESEARCH

The impact of production structure changes in China's manufacturing industry on CO_2 emissions: an extended input–output subsystem and decomposition analysis

Liuguo Shao[1,2] · Jixin Wen[1] · Jiajun Yang[1] · Xunpeng Shi[3] · Manzhi Liu[4]

Received: 4 September 2025 / Accepted: 6 April 2026 / Published online: 4 May 2026
© The Author(s) 2026

Abstract

Given that manufacturing consumes more than 50% of China's fossil energy, shifting the manufacturing production structure towards less carbon-intensive processes is a key lever for achieving China's "dual carbon" goals. However, rigorously assessing how those structural changes affect emissions is lacking in evaluations of emissions reductions in downstream sectors—particularly the impact of indirect emissions. This study extends a structural decomposition analysis (SDA) method within a Ghosh input–output subsystem to quantify how shifts in input structure and production technology drive CO_2 emissions across the entire economy, including both direct and indirect emissions. An empirical analysis is conducted on China's manufacturing industry during 2005–2020. The results show that the embodied CO_2 emissions in China's manufacturing forward linkages increased from 2822.5 Mt in 2005 to 5540.8 Mt in 2020. The scale of primary factors in manufacturing exhibited a gradually weakening carbon-promoting effect. The allocation structure effect of primary factors in manufacturing exhibits an inverted "V" trend—demonstrating a carbon-inhibiting effect in 2005–2010 and 2015–2020, but a carbon-promoting effect in 2010–2015. However, the carbon-inhibiting contributions of all sub-effects of the CO_2 emission multiplier for manufacturing direct forward linkages showed a clear trend of weakening or reversal during the 2015–2020 period. This study emphasizes the critical role of manufacturing resource allocation and technological progress of key production linkages for formulating carbon emission reduction policies.

Keywords CO_2 emissions · Ghosh input–output subsystem · Structural decomposition analysis · Manufacturing industry

1 Introduction

As a major global carbon emitter, China is actively fulfilling its responsibility to reduce emissions and is committed to taking more resolute measures to achieve its "dual carbon" goals by 2030 and 2060 respectively (Pan et al., 2022). The manufacturing industry accounts for over 50% of China's end-use energy consumption and is heavily reliant on fossil fuels such as coal and petroleum, resulting in substantial CO_2 emissions (Liu et al., 2021). Controlling and reducing CO_2 emissions from the manufacturing industry is the key to achieving China's "dual carbon" goals and promoting green development. The Action Plan for Green and Low-Carbon Development of the Manufacturing Industry (2025–2027) clearly requires that through optimizing the industrial structure, improving energy efficiency, strengthening technological innovation, and building a green supply chain, the manufacturing industry should be comprehensively promoted to transform into a green and low-carbon development model (State Council of China, 2025). Therefore, quantifying the CO_2 emissions embodied in different industrial linkages and delineating the emission reduction contributions from production structure optimization and low-carbon technology innovation can provide a critical theoretical foundation and

✉ Jixin Wen
wjx199841@icloud.com

✉ Xunpeng Shi
xunpeng.shi@uts.edu.au

1 Business School, Central SouthUniversity, Changsha, China

2 Institute of Metal Resources Strategy, Central South University, Changsha, China

3 Australia-China Relations Institute, University of Technology Sydney, Ultimo, NSW, Australia

4 School of Economics and Management, China University of Mining and Technology, Xuzhou, Jiangsu, China

decision-making support for formulating precise emission reduction policies in the manufacturing industry.

In the process of providing downstream sectors with products or services and generating value added, the manufacturing sector drives CO_2 emissions in its own sector and downstream sectors through forward linkages (Lin et al., 2014; Zhang et al., 2023). These CO_2 emissions are primarily caused by the manufacturing sector's production activities aimed at obtaining value added (i.e., the forward linkages of manufacturing) (Andretti et al., 2024). In order to take effective actions to reduce manufacturing-related CO_2 emissions, it is necessary to quantify the impact of manufacturing forward linkages on CO_2 emissions. Zhang (2010) used the Ghosh model to conduct a structural decomposition analysis of China's production-related CO_2 emissions (1992–2005), identifying manufacturing scale expansion as the primary driver. Feng et al. (2017) attributed China's CO_2 emissions mainly to manufacturing's primary inputs, highlighting substantial indirect emissions from its forward linkages. Nie et al. (2022) constructed an environmentally extended Ghosh model and revealed that the manufacturing industry in China is the key source of cross-sectoral input emissions caused by forward linkages. However, existing studies have not yet distinguished between direct forward linkages (direct suppliers) and indirect forward linkages (indirect suppliers, i.e., suppliers' suppliers) across industries, making it difficult to systematically quantify the differentiated contributions of different linkage tiers in the manufacturing sector to CO_2 emissions. This research gap may prevent policymakers from accurately identifying the emission reduction responsibilities and potentials across different segments of the manufacturing industrial chain, thereby undermining the targeting and effectiveness of carbon emission reduction policies, and may even lead to the omission or misjudgment of critical indirect emission sources.

Within the input–output framework, subsystem analysis can examine how the economic activities of an industry induce pollution emissions throughout the entire economic system, including input–output subsystem analysis based on the Leontief model and input–output subsystem analysis based on the Ghosh model. Specifically, the Leontief model is fundamentally demand-driven. Leontief input–output subsystem analysis can be used to analyze the contribution of an industry's backward linkages (i.e., the pull effect of final demand) to CO_2 emissions (Alcántara & Padilla, 2008). This method has been applied to service industries (Piaggio et al., 2015), construction industries (Alcántara & Padilla, 2021) and energy-intensive industries (Yuan & Zhao, 2016), providing a quantitative basis for the formulation of demand-side emission reduction policies. In contrast, the Ghosh model is supply-driven, with its theoretical core focusing on the allocation of output (Fan et al., 2018). It effectively tracks how primary inputs are transmitted downstream through an economic system via forward linkages. Ghosh input–output subsystem analysis serves as an effective tool for studying the contribution of an industry's forward linkages to CO_2 emissions (Llop & Tol, 2013). For instance, Andrés et al. (2021) applied this approach to Spain's transportation and storage industry, measuring how its forward linkages drive CO_2 emissions in Spain. Because the core economic activity of the manufacturing sector is to generate value-added by supplying intermediate goods to downstream industries, the "supply-allocation" theoretical logic of the Ghosh model aligns perfectly with this sectoral characteristic (Feng et al., 2017). Therefore, based on the analysis framework of Ghosh input–output subsystem, the contribution mechanism of the forward linkages of the manufacturing industry to CO_2 emissions in the economic system can be effectively quantified.

Combining input–output subsystem analysis with SDA can identify key drivers of direct and indirect CO_2 emission changes of the whole economic system caused by an industrial economic activity. Extensive studies have applied the Leontief input–output subsystem analysis combined with SDA to examine the driving factors of CO_2 emissions caused by backward linkages in various industries. Zhang and Liu (2014) combined Leontief input–output subsystem analysis with the SDA method to reveal the driving factors behind changes in CO_2 emissions caused by backward linkages in China's industrial sector, finding that the carbon-inhibiting effect of CO_2 emission intensity was offset by the carbon-promoting effect of demand expansion. In addition, the input–output subsystem and SDA are also used to analyze the specific structural characteristics of CO_2 emissions in the service industry (Butnar & Llop, 2011), the electric power industry (Ma et al., 2019), the transportation industry (Liu et al., 2022a, 2022b), and the information and communication technology industry (Yuan et al., 2024a, 2024b). A decomposition framework integrating Ghosh input–output subsystem and SDA can effectively assess how manufacturing production structure changes drive economy-wide CO_2 emissions. However, no study has yet proposed a comprehensive decomposition analysis framework that integrates these two methods. Moreover, neither the allocation structure of different primary factors in different sectors nor the heterogeneity of carbon reduction technologies with different forward linkages has been considered. This omission may lead to misjudgments on the emission reduction contributions of manufacturing resource allocation and technological progress when formulating relevant emission reduction policies.

To fill the aforementioned research gaps, this study proposes an extended framework integrating Ghosh input–output subsystem analysis with SDA, with its main contributions reflected in the following three aspects. First, by systematically differentiating between direct and indirect forward linkages,

this study constructs an extended Ghosh input–output subsystem analysis method to quantify the contributions to CO_2 emissions from different industrial linkages carried out by the manufacturing industry to obtain value added. Second, by incorporating the allocation structure of primary factors and the CO_2 emission multipliers of different forward linkages into the SDA framework, it reveals the heterogeneous impacts of resource allocation and technological progress across different industrial linkage tiers. Finally, it identifies the specific emission reduction potentials and technological bottlenecks within different manufacturing forward linkages, providing a new and targeted perspective for formulating collaborative carbon mitigation policies across manufacturing-related industrial chains under China's "dual carbon" goals.

The remaining part of this study is as follows: Sect. 2 describes the methodology and data sources; Sect. 3 presents the empirical analysis of China's manufacturing industry from 2005 to 2020; Sect. 4 is a discussion of methodology, empirical results and policy implications.

2 Methods

2.1 Measurement methodology

As a key economic driver, manufacturing production activities of obtaining value added promote the CO_2 emissions both within its own sector and downstream industries. Income-based accounting based on the Ghosh model can effectively capture this part of CO_2 emissions (Zhang, 2010). To isolate the forward linkages of manufacturing from other industries, we adopted the Ghosh input–output subsystem analysis and improved the method (Andrés et al., 2021). Embedding the perspectives of both direct and indirect forward linkages into the Ghosh input–output subsystem helps analyze the component characteristics of CO_2 emissions from different forward linkages in the manufacturing industry, thereby clarifying their contribution mechanisms (Ruiz-Peñalver et al., 2019). Furthermore, we developed a quantitative framework to assess the impact of manufacturing production structure changes on CO_2 emissions using an extended Ghosh input–output subsystem analysis combined with SDA (Yan et al., 2016). All model construction processes in this study are derived from the fundamental equations of the Ghosh model, and the specific derivation process is as follows.

When the economic system is divided into n sectors, the following relationships exist between them:

$$X = \mu Z + V \tag{1}$$

where X represents a $1 \times n$ vector of gross output, whose element x_j denotes the gross output of sector j; Z represents a $n \times n$ matrix of intermediate inputs, whose element z_{ij} indicates the intermediate inputs from sector i to sector j; V represents an $1 \times n$ vector of primary inputs, whose element v_j denotes the primary inputs of sector j. Additionally, μ is a $1 \times n$ summation vector.

The balance relationship of Eq. (1) can be further expressed as the basic equation of Ghosh model:

$$X = V(I - B)^{-1} = VG \tag{2}$$

where B represents a $n \times n$ the direct allocation coefficient matrix, whose element b_{ij} denotes the proportion of output from sector i that is allocated to sector j, expressed as $b_{ij} = \frac{z_{ij}}{X_i}$; G represents an $n \times n$ Ghosh inverse matrix, whose element g_{ij} indicates the increase in gross output of sector i induced by a unit primary inputs in sector j.

Based on Eq. (2), we construct the manufacturing subsystem. We partition matrix B into two groups, S and R, where group S describes the sectors belonging to the manufacturing subsystem, numbered from 1 to k, and group R describes the remaining sectors in the economic system, numbered from $k+1$ to n. Thus, matrix B can be expressed as:

$$B = \begin{pmatrix} B_{SS} & B_{SR} \\ B_{RS} & B_{RR} \end{pmatrix} \tag{3}$$

Then, the matrix G can be expressed as:

$$G = (I - B)^{-1} = \left[\begin{pmatrix} I_{SS} & 0 \\ 0 & I_{RR} \end{pmatrix} - \begin{pmatrix} B_{SS} & B_{SR} \\ B_{RS} & B_{RR} \end{pmatrix} \right]^{-1} = \begin{pmatrix} G_{SS} & G_{SR} \\ G_{RS} & G_{RR} \end{pmatrix} \tag{4}$$

where I_{SS} and I_{RR} are identity matrices.

Let the gross output $X = \begin{pmatrix} X_S & X_R \end{pmatrix}$ and primary inputs $V = \begin{pmatrix} V_S & V_R \end{pmatrix}$. Equation (2) can then be expressed in the following form:

$$\begin{pmatrix} X_S & X_R \end{pmatrix} = \begin{pmatrix} V_S & V_R \end{pmatrix} \begin{pmatrix} G_{SS} & G_{SR} \\ G_{RS} & G_{RR} \end{pmatrix} \tag{5}$$

To isolate the relationship between the manufacturing subsystem and other subsystems, let $V_R = 0$, then:

$$\begin{pmatrix} X_S & X_R \end{pmatrix} = \begin{pmatrix} V_S & 0 \end{pmatrix} \begin{pmatrix} G_{SS} & G_{SR} \\ G_{RS} & G_{RR} \end{pmatrix} = \begin{pmatrix} V_S G_{SS} & V_S G_{SR} \end{pmatrix} \tag{6}$$

V_S can be further expressed as:

$$V_S = {V^h}_S {FS^{hi}}_S \tag{7}$$

where ${V^h}_S$ represents a $1 \times h$ vector of scale of primary factors in manufacturing, and its element ${v^h}_s = \sum_{i=1}^{k} {v^h}_i$, represents the scale of primary factor h. ${v^h}_i$ denotes the scale of primary factor h in manufacturing sector i. ${FS^{hi}}_S$ represents a $h \times i$ matrix of the allocation structure of primary factors in manufacturing, and its element ${fs^{hi}}_s = \frac{{v^h}_i}{{v^h}_s}$, represents the proportion of h-type primary factor required by sector i.

To construct a subsystem capturing CO_2 emissions, let CE_i^p represent the end-use CO_2 emissions of sector i, then the vector C of end-use CO_2 emission coefficient per unit of output can be expressed as (Cansino et al., 2016):

$$C = \left(\frac{CE_1^p}{x_1}, \cdots, \frac{CE_i^p}{x_i}, \cdots, \frac{CE_n^p}{x_n} \right)' \tag{8}$$

where "′" represents the transpose of the vector.

Divide set C into two subsets: the subsystem sectors and other sectors, denoted as $C = \begin{pmatrix} C_S \\ C_R \end{pmatrix}$. The embodied CO_2 emissions in manufacturing forward linkages (i.e., the CO_2 emissions caused by manufacturing forward linkages) denoted as CE_{inc}^S, can be expressed as:

$$\begin{aligned} CE_{inc}^S &= \begin{pmatrix} V^h{}_S FS^{hi}{}_S G_{SS} & V^h{}_S FS^{hi}{}_S G_{SR} \end{pmatrix} \begin{pmatrix} C_S \\ C_R \end{pmatrix} \\ &= V^h{}_S FS^{hi}{}_S G_{SS} C_S + V^h{}_S FS^{hi}{}_S G_{SR} C_R \end{aligned} \tag{9}$$

Since the direct allocation coefficient matrix captures only direct inter-sectoral linkages but omits indirect ones, we note that gross output of economic sectors comprises both direct and indirect output (Ruiz-Peñalver et al., 2019). Therefore, this study divides gross output into direct output and indirect output:

$$\begin{aligned} X &= X_{DS} + X_{IS} = V(I + B) \\ &\quad + V\left[(I - B)^{-1} - (I + B)\right] = V(I + B) \\ &\quad + V[G - (I + B)] \end{aligned} \tag{10}$$

where X_{DS} represents direct output; X_{IS} denotes the indirect output. Therefore, CE_{inc}^S can also be divided into direct and indirect components.

Substituting Eqs. (4) and (10) into Eq. (9) yields:

$$\begin{aligned} CE_{inc}^S &= \underbrace{\begin{pmatrix} V_S^h FS_S^{hi} & 0 \end{pmatrix} \begin{pmatrix} I + B_{SS} & B_{SR} \\ B_{RS} & I + B_{RR} \end{pmatrix} \begin{pmatrix} C_S \\ C_R \end{pmatrix}}_{Direct\ component} \\ &\quad + \underbrace{\begin{pmatrix} V_S^h FS_S^{hi} & 0 \end{pmatrix} \begin{pmatrix} G_{SS} - B_{SS} - I & G_{SR} - B_{SR} \\ G_{RS} - B_{RS} & G_{RR} - B_{RR} - I \end{pmatrix} \begin{pmatrix} C_S \\ C_R \end{pmatrix}}_{Indirect\ component} \end{aligned} \tag{11}$$

where the direct component represents the embodied CO_2 emissions from the direct forward linkages in manufacturing, while the indirect component represents the embodied CO_2 emissions from the indirect forward linkages in manufacturing.

Equation (11) can be specifically expressed as (Andrés et al., 2021):

$$\begin{aligned} CE_{inc}^S &= \underbrace{\underbrace{V_S^h FS_S^{hi} C_S}_{SC} + \underbrace{V_S^h FS_S^{hi} B_{SS} C_S}_{DINC} + \underbrace{V_S^h FS_S^{hi} B_{SR} C_R}_{DSOC}}_{Direct\ component} \\ &\quad + \underbrace{\underbrace{V_S^h FS_S^{hi} (G_{SS} - B_{SS} - I) C_S}_{IINC} + \underbrace{V_S^h FS_S^{hi} (G_{SR} - B_{SR}) C_R}_{ISOC}}_{Indirect\ component} \end{aligned} \tag{12}$$

where *IINC* is defined as an indirect internal component, representing the embodied CO_2 emissions from the indirect forward linkages within manufacturing. Notably, *IINC* encompasses not only the indirect forward linkages between sectors within manufacturing but also the feedback effects formed through indirect forward linkages between manufacturing and other industries. Disentangling these two components may yield more targeted policy implications. Therefore, we proceed to consider the submatrix G_{SS} of the Ghosh inverse matrix. Multiplying the matrix $(I - B)$ by the matrix G yields: $I = (I - B)G = \begin{pmatrix} I_{SS} - B_{SS} & -B_{SR} \\ -B_{RS} & I_{RR} - B_{RR} \end{pmatrix} \begin{pmatrix} G_{SS} & G_{SR} \\ G_{RS} & G_{RR} \end{pmatrix}$, then $I_{SS} = (I_{SS} - B_{SS}) G_{SS} - B_{SR} G_{RS}$, so we can decompose G_{SS} into two parts:

$$G_{SS} = (I_{SS} - B_{SS})^{-1} + (I_{SS} - B_{SS})^{-1} B_{SR} G_{RS} \tag{13}$$

Substituting Eq. (13) into Eq. (12), *IINC* can be decomposed into two new components:

$$CE_{inc}^S = \underbrace{\underbrace{V_S^h FS_S^{hi} C_S}_{SC} + \underbrace{V_S^h FS_S^{hi} B_{SS} C_S}_{DINC} + \underbrace{V_S^h FS_S^{hi} B_{SR} C_R}_{DSOC}}_{Direct\ component} + \underbrace{\underbrace{V_S^h FS_S^{hi} \left[(I_{SS} - B_{SS})^{-1} - B_{SS} - I_{SS} \right] C_S}_{IISC} + \underbrace{V_S^h FS_S^{hi} (I_{SS} - B_{SS})^{-1} B_{SR} G_{RS} C_S}_{FC} + \underbrace{V_S^h FS_S^{hi} (G_{SR} - B_{SR}) C_R}_{ISOC}}_{Indirect\ component} \tag{14}$$

Therefore, CE_{inc}^S can be further decomposed into six components:

- The scale component (*SC*) represents the CO_2 emissions directly generated when the manufacturing industry uses its primary inputs for production. It measures the direct CO_2 emissions caused by the production scale of the manufacturing industry.
- The direct internal component (*DINC*) represents the CO_2 emissions embodied in the direct forward linkages between sectors within the manufacturing industry. It measures the CO_2 emissions caused by direct intermediate inputs between manufacturing sectors.
- The direct spillover component (*DSOC*) represents the CO_2 emissions embodied in the direct forward linkages from the manufacturing industry to other industries. It measures the CO_2 emissions caused by direct intermediate inputs supplied by the manufacturing industry to other industries (Freire-González & Canosa, 2024).
- The indirect spillover component (*ISOC*) represents the CO_2 emissions embodied in the indirect forward linkages from the manufacturing industry to other industries. It measures the CO_2 emissions caused by indirect intermediate inputs supplied by the manufacturing industry to other industries.
- The indirect internal supply component (*IISC*) represents the CO_2 emissions embodied in the indirect forward linkages between sectors within the manufacturing industry. It measures the CO_2 emissions caused by indirect intermediate inputs between manufacturing sectors.
- The feedback component (*FC*) represents the CO_2 emissions embodied in the cross-industry indirect forward linkages between manufacturing sectors. It measures the CO_2 emissions caused by cross-industry indirect intermediate inputs between manufacturing sectors.

As shown in Fig. 1, the embodied CO_2 emissions in manufacturing forward linkages can be systematically categorized from multiple dimensions. Firstly, based on direct and indirect forward linkages between sectors, the six components can be divided into direct component (including *SC*, *DINC*, and *DSOC*) and indirect component (including *IISC*, *FC*, and *ISOC*). Secondly, according to the patterns of

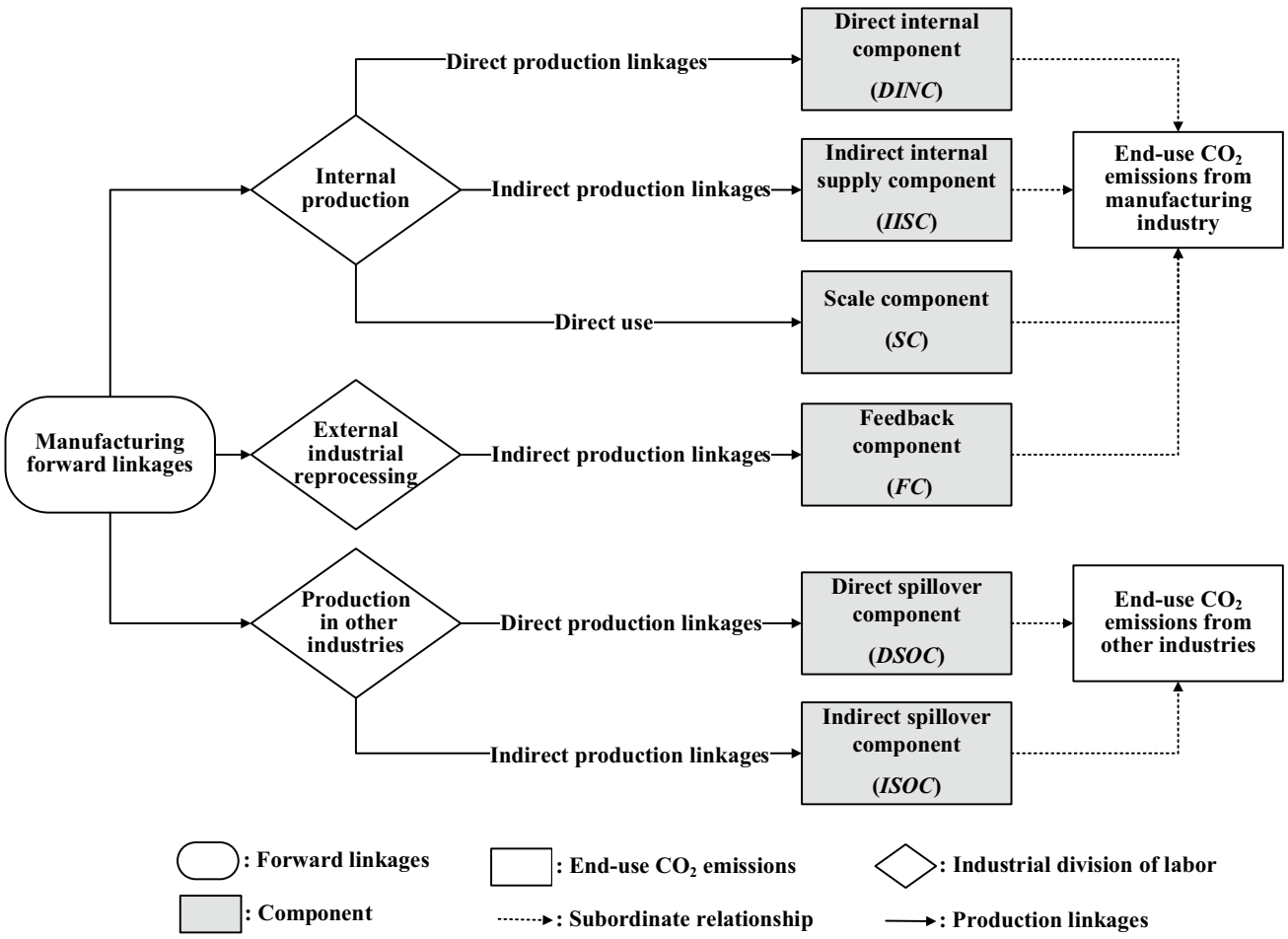

Fig. 1 Framework for the contribution of manufacturing forward linkages to CO_2 emissions

industrial division of labor, these components can be further classified into three categories: internal production (reflecting activities within the manufacturing industry, including *SC*, *DINC*, and *IISC*), external industrial reprocessing (reflecting cross-industry circular feedback, including *FC*), and production in other industries (reflecting the direct and indirect driving effects of manufacturing on other industries, including *DSOC* and *ISOC*) (Andrés et al., 2021). Additionally, they can be categorized into end-use CO_2 emissions from manufacturing (including *DINC*, *IISC*, *SC* and *FC*) and end-use CO_2 emissions from other industries (including *DSOC* and *ISOC*) (Cansino et al., 2016). This multidimensional classification framework reveals the structural characteristics of CO_2 emissions driven by different forward linkages of the manufacturing industry across the entire industrial system.

The Ghosh input–output subsystem analysis reveals the contribution patterns of different manufacturing forward linkages to CO_2 emissions. Further combined with SDA, it enables the quantification of the impacts of manufacturing resource allocation and technological progress on CO_2 emissions (Su & Ang, 2016; Zhang, 2010). Therefore, the changes in embodied CO_2 emissions from China's manufacturing forward linkages (ΔCE^S_{inc}) can be expressed as the sum of changes in the six components:

$$\Delta CE^S_{inc} = \Delta SC + \Delta DINC + \Delta DSOC + \Delta IISC + \Delta FC + \Delta ISOC \tag{15}$$

Combining Eqs. (14) and (15), the contribution of changes in each driving factor to ΔCE^S_{inc}:

$$\Delta CE^S_{inc} = \sum_r \Delta PFS_r + \sum_r \Delta PFE_r + \sum_r \Delta CEE_r, \quad r \in \{SC, DINC, DSOC, IISC, FC, ISOC\} \tag{16}$$

where $\Delta PFS = \sum_r \Delta PFS_r$, represents the total contribution of the scale of primary factors in manufacturing to ΔCE^S_{inc}, and $\Delta PFE = \sum_r \Delta PFE_r$, represents the total contribution of the allocation structure of primary factors in manufacturing to ΔCE^S_{inc}. These two indicators reflect the impact of manufacturing resource allocation on CO_2 emissions (Wang et al., 2020). $\Delta CEE = \sum_r \Delta CEE_r$, represents the total contribution of changes in the CO_2 emission multiplier for manufacturing forward linkages—which measures the CO_2 emission efficiency of these linkages—to ΔCE^S_{inc} (Zhang, 2010). Based on the embodied CO_2 emission components of different manufacturing forward linkages, the CO_2 emission multiplier for manufacturing forward linkages can be further decomposed into two sub-effects: the CO_2 emission multiplier for manufacturing direct forward linkages and the CO_2 emission multiplier for manufacturing indirect forward linkages. Among them, the sub-effects of the CO_2 emission multiplier for manufacturing direct forward linkages include the CO_2 emission intensity in manufacturing sectors, the CO_2 emission multiplier of direct forward linkages between sectors within manufacturing, and the CO_2 emission multiplier of direct forward linkages from manufacturing to other industries. The sub-effects of the CO_2 emission multiplier for manufacturing indirect forward linkages include the CO_2 emission multiplier of indirect forward linkages between sectors within manufacturing, the CO_2 emission multiplier in cross-industry indirect forward linkages of manufacturing sectors, and the CO_2 emission multiplier of indirect forward linkages from manufacturing to other industries. Specifically, the CO_2 emission intensity in manufacturing sectors reflects the direct CO_2 emission efficiency during the production process of the manufacturing sector. The five different forward linkage CO_2 emission multipliers reflect the level of technology for coordinated emission reduction in the industrial chain associated with the forward linkages of the manufacturing industry (Wang et al., 2018). The driving factors and corresponding mathematical expressions for changes in each component are presented in Table 1.

2.2 Data sources

The input–output tables of China for 2005, 2010, 2015, and 2020 at current prices used in this study are sourced from China's National Bureau of Statistics and are uniformly adjusted to 38 sectors. It should be noted that all model calculations in this study are conducted at the level of 38 sectors. To reveal the forward linkages between manufacturing and other industries, the sectors in the input–output table are grouped into six industry categories according to the 2017 National Industrial Classification of Economic Activities (GB/T 4754-—2017) (see Table S1 in the Supplementary Information SI1). To eliminate the impact of price factors on this study, we adopted the price index reduction method proposed by Liu and Peng (2010). Using current-price input–output tables as the benchmark, we compiled comparable-price input–output tables with 2005 as the price base year. All price indices used were obtained from the China Statistical Yearbook (see Table S2 in the Supplementary Information SI1 for the price indices). Since the input–output tables of 2005, 2010 and 2015 are competitive, they are divided into non-competitive input–output tables by referring to the splitting method of Wang et al. (2022). Considering that CO_2 emissions in China are mainly caused by fossil energy consumption, we evaluate the CO_2 emissions from energy consumption (Su et al., 2017). The energy consumption data come from China Energy Statistical Yearbook (2021), and the energy consumption of various industries is measured in physical quantities. All CO_2 emissions in this study are expressed in million tons (Mt).

Table 1 Driving factors and expressions of changes in each component

Component changes	Driving factor	Expression
ΔSC	Scale of primary factors in manufacturing	$\Delta PFS_{SC} = \frac{1}{2}\Delta V^h{}_S\left(FS^{hi}{}_S{}^0 C_S{}^0 + FS^{hi}{}_S{}^T C_S{}^T\right)$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{SC} = \frac{1}{2}\left(V^h{}_S{}^T \Delta FS^{hi}{}_S C_S{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S C_S{}^T\right)$
	CO_2 emission intensity in manufacturing sectors	$\Delta CEE_{SC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta C_S$
$\Delta DINC$	Scale of primary factors in manufacturing	$\Delta PFS_{DINC} = \frac{1}{2}\Delta V^h{}_S\left(FS^{hi}{}_S{}^0 B_{SS}{}^0 C_S{}^0 + FS^{hi}{}_S{}^T B_{SS}{}^T C_S{}^T\right)$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{DINC} = \frac{1}{2}\left(V^h{}_S{}^T \Delta FS^{hi}{}_S B_{SS}{}^0 C_S{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S B_{SS}{}^T C_S{}^T\right)$
	CO_2 emission multiplier of direct forward linkages between sectors within manufacturing	$\Delta CEE_{DINC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta(B_{SS}C_S)$
$\Delta DSOC$	Scale of primary factors in manufacturing	$\Delta PFS_{DSOC} = \frac{1}{2}\Delta V^h{}_S\left(FS^{hi}{}_S{}^0 B_{SR}{}^0 C_R{}^0 + FS^{hi}{}_S{}^T B_{SR}{}^T C_R{}^T\right)$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{DSOC} = \frac{1}{2}\left(V^h{}_S{}^T \Delta FS^{hi}{}_S B_{SR}{}^0 C_R{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S B_{SR}{}^T C_R{}^T\right)$
	CO_2 emission multiplier of direct forward linkages from manufacturing to other industries	$\Delta CEE_{DSOC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta(B_{SR}C_R)$
$\Delta IISC$	Scale of primary factors in manufacturing	$\Delta PFS_{IISC} = \frac{1}{2}\Delta V^h{}_S\left\{FS^{hi}{}_S{}^0\left[\left(I_{SS} - B_{SS}\right)^{-1} - B_{SS} - I_{SS}\right]^0 C_S{}^0 + FS^{hi}{}_S{}^T\left[\left(I_{SS} - B_{SS}\right)^{-1} - B_{SS} - I_{SS}\right]^T C_S{}^T\right\}$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{IISC} = \frac{1}{2}\left\{V^h{}_S{}^T \Delta FS^{hi}{}_S\left[\left(I_{SS} - B_{SS}\right)^{-1} - B_{SS} - I_{SS}\right]^0 C_S{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S\left[\left(I_{SS} - B_{SS}\right)^{-1} - B_{SS} - I_{SS}\right]^T C_S{}^T\right\}$
	CO_2 emission multiplier of indirect forward linkages between sectors within manufacturing	$\Delta CEE_{IISC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta\left\{\left[\left(I_{SS} - B_{SS}\right)^{-1} - B_{SS} - I_{SS}\right]C_S\right\}$
ΔFC	Scale of primary factors in manufacturing	$\Delta PFS_{FC} = \frac{1}{2}\Delta V^h{}_S\left\{FS^{hi}{}_S{}^0\left[\left(I_{SS} - B_{SS}\right)^{-1} B_{SR}G_{RS}\right]^0 C_S{}^0 + FS^{hi}{}_S{}^T\left[\left(I_{SS} - B_{SS}\right)^{-1} B_{SR}G_{RS}\right]^T C_S{}^T\right\}$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{FC} = \frac{1}{2}\left\{V^h{}_S{}^T \Delta FS^{hi}{}_S\left[\left(I_{SS} - B_{SS}\right)^{-1} B_{SR}G_{RS}\right]^0 C_S{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S\left[\left(I_{SS} - B_{SS}\right)^{-1} B_{SR}G_{RS}\right]^T C_S{}^T\right\}$
	CO_2 emission multiplier in cross-industry indirect forward linkages of manufacturing sectors	$\Delta CEE_{FC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta\left\{\left[\left(I_{SS} - B_{SS}\right)^{-1} B_{SR}G_{RS}\right]C_S\right\}$
$\Delta ISOC$	Scale of primary factors in manufacturing	$\Delta PFS_{ISOC} = \frac{1}{2}\Delta V^h{}_S\left[FS^{hi}{}_S{}^0\left(G_{SR} - B_{SR}\right)^0 C_R{}^0 + FS^{hi}{}_S{}^T\left(G_{SR} - B_{SR}\right)^T C_R{}^T\right]$
	Allocation structure of primary factors in manufacturing	$\Delta PFE_{ISOC} = \frac{1}{2}\left[V^h{}_S{}^T \Delta FS^{hi}{}_S\left(G_{SR} - B_{SR}\right)^0 C_R{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S\left(G_{SR} - B_{SR}\right)^T C_R{}^T\right]$
		$\Delta PFE_{ISOC} = \frac{1}{2}\left[V^h{}_S{}^T \Delta FS^{hi}{}_S\left(G_{SR} - B_{SR}\right)^0 C_R{}^0 + V^h{}_S{}^0 \Delta FS^{hi}{}_S\left(G_{SR} - B_{SR}\right)^T C_R{}^T\right]$
	CO_2 emission multiplier of indirect forward linkages from manufacturing to other industries	$\Delta CEE_{ISOC} = \frac{1}{2}\left(V^h{}_S{}^T FS^{hi}{}_S{}^T + V^h{}_S{}^0 FS^{hi}{}_S{}^0\right)\Delta\left[\left(G_{SR} - B_{SR}\right)C_R\right]$

"T" and "0" represent the final value and the initial value respectively

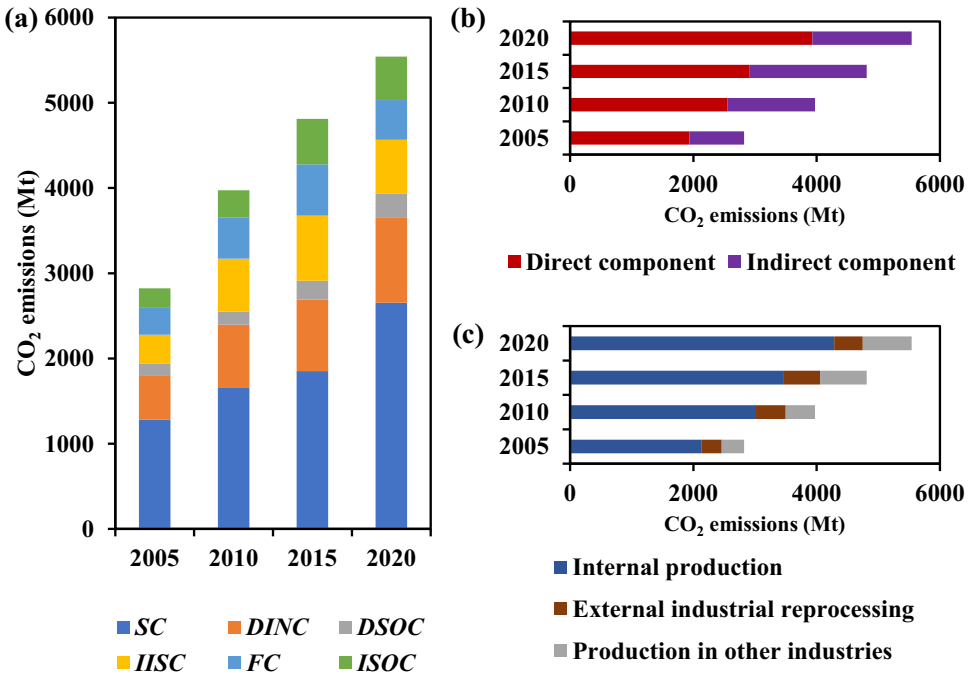

Fig. 2 Embodied CO_2 emissions from different forward linkages in China's manufacturing industry. **a** The six components; **b** The direct and indirect components; **c** The three types of industrial division of labor. Underlying data for this figure are available in Supplementary Information SI2

3 Results

3.1 Analysis of embodied CO_2 emissions in different forward linkages of China's manufacturing industry

Figure 2 illustrates the embodied CO_2 emissions from different forward linkages in China's manufacturing industry. The embodied CO_2 emissions in China's manufacturing forward linkages increased from 2822.5 in 2005 to 5540.8 Mt in 2020, with an increase of 96.3%, indicating that the manufacturing industry has significantly boosted CO_2 emissions across the entire economic system through forward linkages (Fig. 2a). Specifically, *SC* contributed most significantly, increasing from 1284.1 to 2655.6 Mt over this period. This growth was primarily attributed to the rapid expansion of manufacturing production scale (Fergus & Nicholas, 2017). *DINC* followed *SC*, rising from 511.9 in 2005 to 993.2 Mt in 2020. This indicates that direct forward linkages among sectors within China's manufacturing industry have led to a significant increase in CO_2 emissions. Although *DSOC* was not a major source of emissions, its contribution gradually increased, indicating that the carbon emission spillover effects of China's manufacturing industry on its downstream industries through direct forward linkages have been progressively strengthening. Notably, *IISC*, *FC*, and *ISOC* all showed continuous growth from 2005 to 2015 but declined from 2015 to 2020. This indicates that during the 13th Five-Year Plan period (2015–2020), China achieved significant success in curbing the embodied CO_2 emissions from indirect forward linkages in the manufacturing industry.

In terms of direct and indirect linkages, the direct component remained the primary source of emissions, rising from 1937.0 in 2005 to 3931.4 Mt in 2020 (Fig. 2b). According to the industrial division of labor pattern, internal production also dominated, with its emissions increasing from 2137.2 in 2005 to 4284.4 Mt in 2020 (Fig. 2c). The analysis of embodied CO_2 emissions from forward linkages between China's manufacturing industry and other industries can be found in Part II of Supplementary Information SI1. In summary, optimizing the internal production structure and regulating direct forward carbon linkages both within and across industries represent two critical priorities for China's manufacturing industry to achieve systemic emission reduction.

3.2 Decomposition analysis of changes in total emissions

Figure 3 presents the decomposition results of changes in embodied CO_2 emissions from China's manufacturing forward linkages from 2005 to 2020. The scale of primary factors in manufacturing exhibited a gradually weakening yet dominant carbon-promoting effect. Its contribution to the growth rate of embodied CO_2 emissions in China's manufacturing forward linkages (hereafter collectively referred to as the contribution rate) decreased from 92.4% during 2005–2010 to 29.1% during 2015–2020. This reflects that the model of manufacturing relying on increasing primary inputs to drive economic growth is significantly weakening its pull on the growth in CO_2 emissions. The allocation structure effect of primary factors in manufacturing showed an inverted "V" trend. Its contribution rate increased from

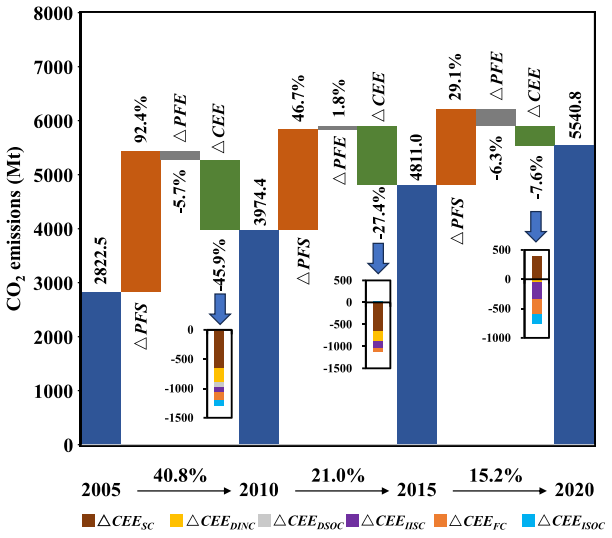

Fig. 3 Decomposition of changes in embodied CO_2 emissions from China's manufacturing forward linkages. Underlying data for this figure are available in Supplementary Information SI2

-5.7% during 2005–2010 to 1.8% during 2010–2015, subsequently declining to − 6.3% during 2015–2020. This demonstrates that during the 2015–2020 period, China's manufacturing industry significantly suppressed the growth of CO_2 emissions by optimizing the factor allocation structure, even exceeding the level of suppression achieved in the 2005–2010 period.

The CO_2 emission multiplier for manufacturing forward linkages consistently demonstrated a gradually weakening but dominant carbon-inhibiting effect, with its contribution rate increasing from − 45.9% during 2005–2010 to − 7.6% during 2015–2020. This indicates that although technological progress in the industrial chains related to manufacturing forward linkages continuously contributed to emission reductions, its mitigating effect has significantly weakened. Further decomposition of this multiplier reveals that the carbon-inhibiting contributions of both ΔCEE_{DINC} and ΔCEE_{DSOC} showed a declining trend, persistently driving the attenuation of the carbon-inhibiting effect of the CO_2 emission multiplier for manufacturing forward linkages. Particularly, the shift of ΔCEE_{SC} to a carbon-promoting effect during 2015–2020 (with a contribution value of 396.8 Mt) emerged as the primary reason for the sharp decline in the carbon-inhibiting contribution of the CO_2 emission multiplier for manufacturing forward linkages in this phase. Meanwhile, ΔCEE_{FC} and ΔCEE_{ISOC} further exacerbated this attenuation trend during 2010–2015, particularly as ΔCEE_{ISOC} shifted to a carbon-promoting effect in this period (with a contribution value of 33.8 Mt). In contrast, ΔCEE_{IISC} exhibited a progressively strengthening carbon-inhibiting effect, with its contribution value decreasing from − 73.1 Mt during 2005–2010 to − 282.8 Mt during 2015–2020. Additionally, both ΔCEE_{FC} and ΔCEE_{ISOC} demonstrated significant carbon-inhibiting effects during 2015–2020 (with contribution values of − 266.1 Mt and − 155.7 Mt, respectively). These results not only elucidate the reasons for the attenuation of the carbon-inhibiting effect of the CO_2 emission multiplier for manufacturing forward linkages but also quantify the differential emission reduction potential of technological progress across various forward linkage-related industrial chains in manufacturing.

3.3 Decomposition analysis of changes in each component

To further identify the driving factors of embodied CO_2 emissions across different manufacturing forward linkages, this study conducted a decomposition analysis of the embodied CO_2 emissions for the direct and indirect components, the three types of industrial division of labor, and the six detailed forward linkage components. Synthesizing the results from Figs. 4, 5 and 6, the scale of primary factors in manufacturing exhibited the most significant carbon-promoting effect on the growth of all components. However, this dominant carbon-promoting effect has been gradually weakening. For instance, its contribution rates to the direct and indirect components significantly decreased from 89.9 and 98.0% during 2005–2010 to 32.5 and 23.7% during 2015–2020, respectively (Fig. 4a). During the same period, its contribution rate to the growth of embodied CO_2 emissions from internal production also declined from 92.4 to 30.5% (Fig. 5a). This confirms that all forward linkages within China's manufacturing industry are progressively reducing their reliance on the scale expansion of primary inputs. Aside from its continuously strengthening carbon-inhibiting effect on *DINC* and *IISC*, the inverted "V"-shaped trend of the allocation structure effect of primary factors in manufacturing, observed at the aggregate level, was also a universal characteristic across the remaining sub-components (Figs. 6a and b). In particular, ΔPFE_{SC} and ΔPFE_{ISOC} exhibited carbon-promoting effects on *SC* and *ISOC* during 2010–2015, with contribution rates of 5.5 and 0.2%, respectively (Figs. 6c and d). However, this trend fundamentally reversed during 2015–2020, as the allocation structure of primary factors in manufacturing exerted a significant carbon-inhibiting effect across all sub-components. Notably, this effect substantially suppressed the growth of *SC*, yielding a contribution value of − 224.4 Mt. This highlights the critical role of resource allocation optimization in driving emission reductions across manufacturing-related industrial chains during the 13th Five-Year Plan period.

The CO_2 emission multiplier for manufacturing forward linkages (i.e., the technological progress effect) exhibited different evolutionary trajectories across various breakdown

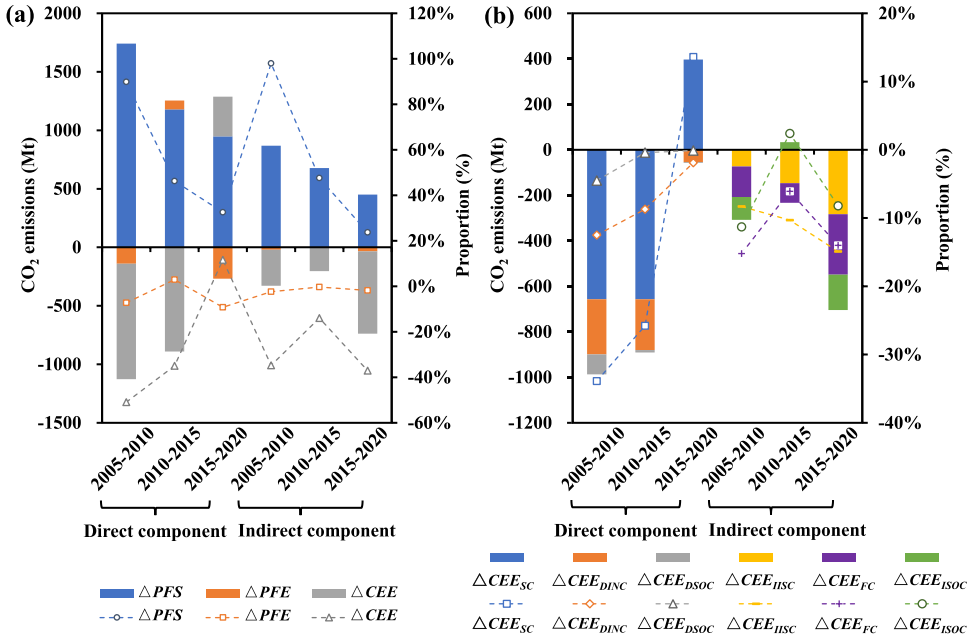

Fig. 4 Decomposition of changes in direct and indirect components. **a** Decomposition of direct and indirect components; **b** Contributions of the sub-effects of CO_2 emission multiplier for manufacturing forward linkages to changes in the direct and indirect components. Underlying data for this figure are available in Supplementary Information SI2

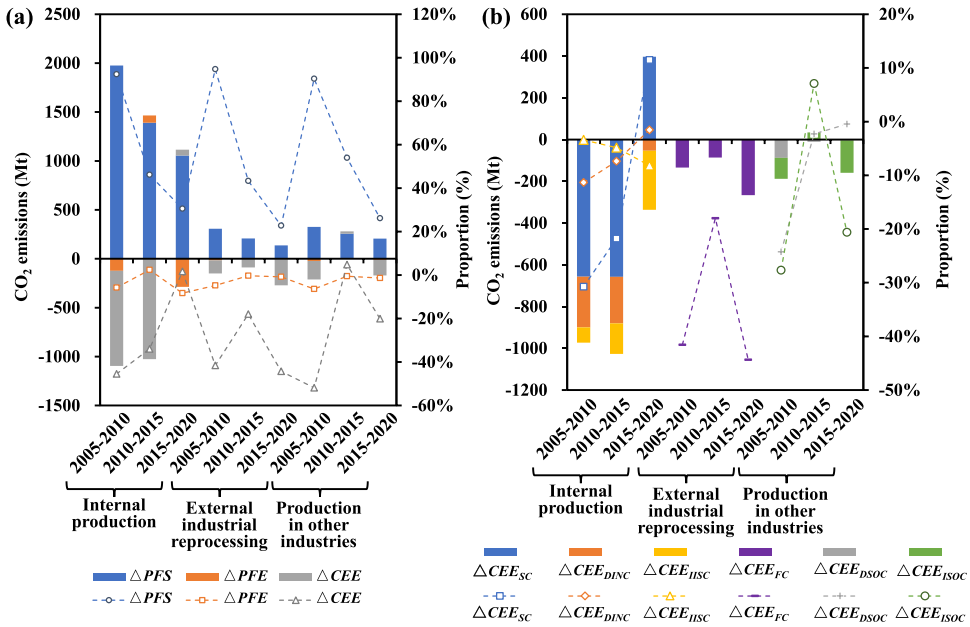

Fig. 5 Decomposition of changes in components of three types of industrial division of labor. **a** Decomposition of changes in components of three types of industrial division of labor; **b** Contributions of the sub-effects of CO_2 emission multiplier for manufacturing forward linkages to changes in components of three types of industrial division of labor. Underlying data for this figure are available in Supplementary Information SI2

dimensions. As shown in Fig. 4b, the impact of the CO_2 emission multiplier for manufacturing direct forward linkages on the direct component shifted from a carbon-inhibiting effect to a carbon-promoting effect, with its contribution rate increasing from − 51.0% during 2005–2010 to 11.6% during 2015–2020. Among its sub-effects, the impact of ΔCEE_{SC} on the direct component transitioned from a carbon-inhibiting effect to a carbon-promoting effect, with its contribution rate rising from -33.9% during 2005–2010 to 13.6% during 2015–2020, whereas ΔCEE_{DINC} and ΔCEE_{DSOC} both exhibited a persistently declining carbon-inhibiting effect (weakening substantially during 2015–2020 and 2010–2015, respectively) (Fig. 6e). This suggests that during the 13th Five-Year Plan period, the progress in carbon reduction technologies within manufacturing direct forward linkages may have encountered a bottleneck, posing a technological challenge for achieving systematic emission reductions. Notably, the reversal of ΔCEE_{SC} was also the primary reason prompting the CO_2 emission multiplier for manufacturing forward linkages to exhibit a significant carbon-promoting

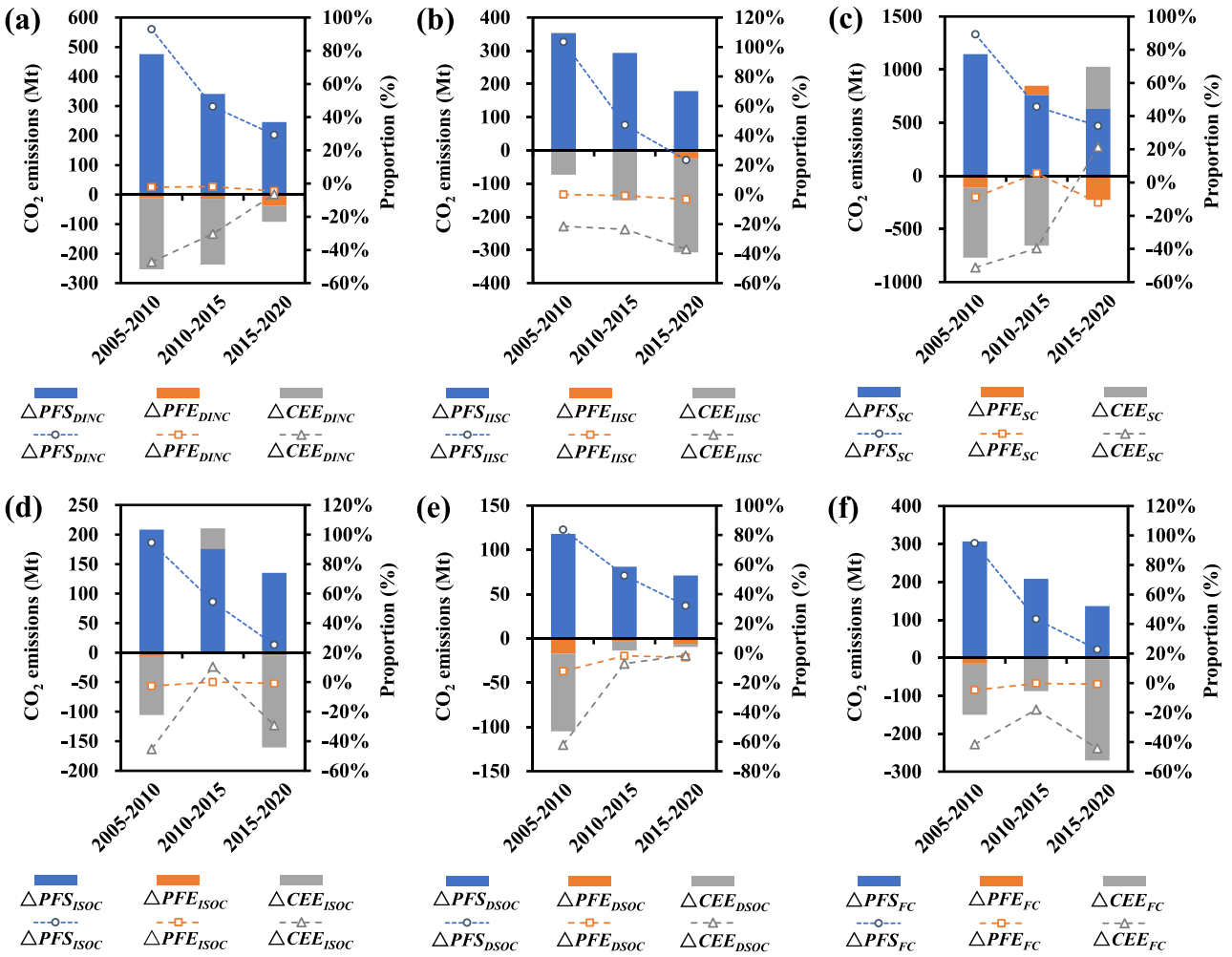

Fig. 6 Decomposition of the changes of each component. **a** *SC*; **b** *DINC*; **c** *DSOC*; **d** *IISC*; **e** *FC*; **f** *ISOC*. Underlying data for this figure are available in Supplementary Information SI2

effect on internal production during 2015–2020, as its contribution rate to internal production increased from − 30.8% during 2010–2015 to 11.5% during 2015–2020 (Fig. 5b). These findings indicate that carbon emission reduction policies targeting internal production in manufacturing should prioritize improving the direct CO_2 emission efficiency of manufacturing sectors.

In contrast to the technological sluggishness in the direct linkages, the CO_2 emission multiplier for manufacturing forward linkages consistently maintained a carbon-inhibiting effect on the indirect component, reaching a high contribution rate of − 37.1% during 2015–2020. This strong resilience was jointly driven by its sub-effects: First, the carbon-inhibiting effect of ΔCEE_{IISC} continuously strengthened, with its contribution rate to the indirect component decreasing from − 8.3 during 2005–2010 to − 14.9% during 2015–2020 (Fig. 4b), and its contribution rate to its corresponding component *IISC* decreasing even further from − 21.4% to − 37.0%. Second, although ΔCEE_{FC} and ΔCEE_{ISOC} exhibited inverted "V"-shaped fluctuations (with ΔCEE_{ISOC} showing a carbon-promoting effect during 2010–2015), they both demonstrated significant carbon-inhibiting effects during 2015–2020 (Fig. 6f). These three core sub-effects jointly constituted the key driving force behind the decline of the indirect CO_2 emission component during 2015–2020. The decomposition analysis of changes in embodied CO_2 emissions from forward linkages between manufacturing and other industries can be found in Part III of Supplementary Information SI1.

4 Discussion

This study identifies the contribution of manufacturing production activities aimed at obtaining value added to CO_2 emissions and decomposes these emissions into six components based on different forward linkages in manufacturing. This approach clarifies the structural association characteristics between manufacturing forward linkages and CO_2 emissions. Compared with existing studies, this research treats the manufacturing industry as both a direct and indirect supplier, and more carefully considers the CO_2 emissions embodied in the direct and indirect intermediate inputs between sectors within manufacturing and between manufacturing and other industries (Andrés et al., 2021). From 2015 to 2020, the embodied CO_2 emissions from direct forward linkages in China's manufacturing industry increased significantly, which was mainly attributed to the use of primary inputs and internal direct intermediate inputs in China's manufacturing industry (Li et al., 2024). Moreover, the CO_2 emissions embodied in forward linkages from manufacturing to services have gradually increased, while those from manufacturing to mining have gradually decreased. This trend aligns with the direction of China's industrial restructuring (Wu et al., 2024).

Building upon the component analysis, this study introduces SDA to quantify the impact of changes in China's manufacturing production structure on CO_2 emissions. Notably, the progress in carbon reduction technologies within manufacturing direct forward linkages may have encountered a bottleneck from 2005 to 2015, especially as the contribution of the CO_2 emission intensity of manufacturing sectors to the scale component shifted to a carbon-promoting effect during this period. The decline of the CO_2 emission intensity effect in manufacturing sectors is closely tied to a slowdown in energy efficiency gains and the rigidity of the energy mix. From 2005 to 2015, China achieved massive emission reductions by phasing out outdated production capacities and deploying basic energy-saving equipment (Liu et al., 2022a, 2022b). However, from 2015 to 2020, influenced by factors such as the COVID-19 pandemic and the concentrated release of petrochemical production capacity, energy efficiency improvements in manufacturing slowed down, leading to relatively lagging progress in emission reduction efforts (Wang et al., 2022). Furthermore, without the large-scale commercialization of deep decarbonization technologies (e.g., hydrogen metallurgy, carbon capture and storage) and a fundamental shift away from coal in the core energy mix of heavy industry, the direct CO_2 emission efficiency inevitably hit a structural bottleneck. Indirect linkages span much longer value chains, which are characterized by higher industrial network complexity and deeper cross-sectoral integration (Zhang et al., 2023). From 2015 to 2020, China vigorously promoted industrial digitalization, supply chain management optimization, and the deep integration of the manufacturing and service sectors. These systemic and structural innovations significantly enhanced the comprehensive CO_2 emission efficiency across the extended supply networks, thereby driving the progress of carbon reduction technologies in manufacturing indirect forward linkages during this stage.

Based on the accounting and decomposition results presented above, this study proposes the following targeted policy implications: First, the government should continue to deepen supply-side structural reforms. Policy designs should leverage differentiated credit quotas and environmental taxes to precisely guide primary production factors (such as capital and labor) away from high-carbon upstream intermediate goods manufacturing. Accelerating their reallocation toward low-carbon, high-value-added advanced manufacturing will continuously amplify the emission reduction dividends derived from the optimization of factor allocation. Second, policy targets must precisely focus on the internal production processes of upstream heavy and chemical industries (e.g., steel and petrochemicals). It is recommended that the government establish special "deep decarbonization" funds, pooling resources to achieve breakthroughs in disruptive frontier technologies such as hydrogen metallurgy, carbon capture, utilization, and storage (CCUS), and industrial electrification. This will forcefully shatter the direct energy efficiency "ceiling" within core manufacturing processes. Finally, the scope of emission reduction policies should expand from exclusively targeting individual "major direct emitters" to fostering "whole-industry-chain synergy". It is advised to vigorously promote industrial digitalization and the development of green supply chain management systems, alongside establishing cross-sectoral carbon footprint tracking and accounting platforms. By fully leveraging the green procurement demands of downstream service industries, advanced manufacturing sectors, and end-consumer markets, policymakers can compel mid- and upstream traditional manufacturing segments to implement cleaner production transformations. This approach will further stimulate and amplify the carbon-inhibiting multiplier effect of the indirect forward linkage networks.

5 Supplementary Information

Supplemental Information SI1: This supplementary information provides details about the data replenishment and further analysis of the results.

Supplemental Information S12: This supplementary information provides data evidence to support the statements in the main text, and the data to produce the figures and tables.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s44498-026-00078-0.

Author contribution Liuguo Shao: Investigation, Project administration, Conceptualization, Funding acquisition, Formal analysis, Supervision. Jixin Wen: Investigation, Conceptualization, Methodology, Formal analysis, Writing original draft, Data curation Jiajun Yang: Project administration, Data curation, Formal analysis, Software. Xunpeng Shi: Investigation, Methodology, Formal analysis, Supervision, Data curation, Writing original draft. Manzhi Liu: Project administration, Data curation, Formal analysis.

Funding Open Access funding enabled and organized by CAUL and its Member Institutions. This research is financially supported by Major Projects of the National Social Science Foundation (22&ZD098), Deepland national science and technology major project (2024ZD1002002), Central South University Graduate Students Independent Exploration and Innovation Project (2024ZZTS0337).

Data availability The data that support the findings of this study are openly available in China's National Bureau of Statistics database at https://data.stats.gov.cn/.

Declarations

Conflict of interest The authors declare no competing interests.

Open Access This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit http://creativecommons.org/licenses/by/4.0/.

References

Alcántara, V., & Padilla, E. (2008). Input–output subsystems and pollution: An application to the service sector and CO_2 emissions in Spain. *Ecological Economics, 68*(3), 905–914.

Alcántara, V., & Padilla, E. (2021). CO_2 emissions of the construction sector in Spain during the real estate boom: Input–output subsystem analysis and decomposition. *Journal of Industrial Ecology, 25*(5), 1272–1283.

Andrés, L., Alcántara, V., & Padilla, E. (2021). Transportation, storage and GHG emissions: A new perspective of input-output subsystem analysis. *Transportation Research Part D, 90*, 102646.

Andretti, B., Vieites, Y., Guilherme, A. R., Elmor, L., & Eduardo, B. A. (2024). Underestimations of the income-based ecological footprint inequality. *Climatic Change, 177*(4), 66.

Butnar, I., & Llop, M. (2011). Structural decomposition analysis and input–output subsystems: Changes in CO_2 emissions of Spanish service sectors (2000–2005). *Ecological Economics, 70*(11), 2012–2019.

Cansino, J. M., Román, R., & Ordóez, M. (2016). Main drivers of changes in CO_2 emissions in the Spanish economy: A structural decomposition analysis. *Energy Policy, 89*, 150–159.

Fan, J., Wang, J., Kong, L., & Zhang, X. (2018). The carbon footprints of secondary industry in China: An input-output subsystem analysis. *Natural Hazards, 91*(2), 635–657.

Feng, T., Yang, Y., Xie, S., Dong, J., & Ding, L. (2017). Economic drivers of greenhouse gas emissions in China. *Renewable and Sustainable Energy Reviews, 78*, 996–1006.

Fergus, G., & Nicholas, S. (2017). China's changing economy: Implications for its carbon dioxide emissions. *Climate Policy, 17*(4), 423–442.

Freire-González, J., & Canosa, O. (2024). Economic crises and energy use: An input–output analysis of Catalonia's 2008–2014 financial crisis. *Journal of Industrial Ecology, 29*(1), 185–203.

Li, Q., Wu, S., Liu, Q., & Li, S. (2024). Role of global value chains in embodied domestic CO_2 emissions of China's manufacturing exports: Normal and processing trade heterogeneity. *Energy Economics, 132*, 107346.

Lin, B., Moubarak, M., & Ouyang, X. (2014). Carbon dioxide emissions and growth of the manufacturing sector: Evidence for China. *Energy, 76*, 830–837.

Liu, H., Fan, L., & Shao, Z. (2021). Threshold effects of energy consumption, technological innovation, and supply chain management on enterprise performance in China's manufacturing industry. *Journal of Environmental Management, 300*, 113687.

Liu, M., Wang, J., Wen, J., He, G., Wu, J., Chen, H., & Yang, X. (2022a). Carbon emission and structure analysis of transport industry based on input-output method: China as an example. *Sustainable Production and Consumption, 33*, 168–188.

Liu, M., Wen, J., Meng, Y., Yang, X., Wang, J., Wu, J., & Chen, H. (2022b). Carbon emission structure decomposition analysis of manufacturing industry from the perspective of input-output subsystem: A case study of China. *Environmental Science and Pollution Research, 30*(7), 19012–19029.

Liu, Q., & Peng, Z. (2010). *China's constant price input–output table and relative analysis 1992–2005*. China Statistics Press.

Llop, M., & Tol, R. S. J. (2013). Decomposition of sectoral greenhouse gas emissions: A subsystem input-output model for the Republic of Ireland. *Journal of Environmental Planning and Management, 56*(9), 1316–1331.

Ma, J., Du, G., & Xie, B. (2019). CO_2 emission changes of China's power generation system: Input-output subsystem analysis. *Energy Policy, 124*, 1–12.

Nie, Y., Gao, Y., & He, H. (2022). Modelling structural effect and linkage on carbon emissions in China: An environmentally extended semi-closed Ghosh input–output model. *Energies, 15*(17), 6104–6104.

Pan, A., Zhang, W., Shi, X., & Dai, L. (2022). Climate policy and low-carbon innovation: Evidence from low-carbon city pilots in China. *Energy Economics*. https://doi.org/10.1016/j.eneco.2022.106129

Piaggio, M., Alcantara, V., & Padilla, E. (2015). The materiality of the immaterial service sectors and CO_2 emissions in Uruguay. *Ecological Economics, 110*, 1–10.

Ruiz-Peñalver, S. M., Rodríguez, M., & Camacho, J. A. (2019). A waste generation input output analysis: The case of Spain. *Journal of Cleaner Production, 210*, 1475–1482.

State Council of China. (2025). The Action Plan for Green and Low-Carbon Development of the Manufacturing Industry (2025–2027). https://www.mee.gov.cn/ywdt/szyw/202505/t20250523_1120009.shtml (accessed October 2025).

Su, B., & Ang, B. W. (2016). Multi-region comparisons of emission performance: The structural decomposition analysis approach. *Ecological Indicators, 67*, 78–87.

Su, B., Ang, B. W., & Li, Y. (2017). Input-output and structural decomposition analysis of Singapore's carbon emissions. *Energy Policy, 105*, 484–492.

Wang, H., Li, R., Zhang, N., Zhou, P., & Wang, Q. (2020). Assessing the role of technology in global manufacturing energy intensity change: A production-theoretical decomposition analysis. *Technological Forecasting & Social Change*. https://doi.org/10.1016/j.techfore.2020.120245

Wang, H., Li, X., Tian, X., Ma, L., Wang, G., Wang, X., Wang, Z., Wang, J., & Yue, Q. (2022). Socioeconomic drivers of China's resource efficiency improvement: a structural decomposition analysis for 1997–2017. *Resources, Conservation & Recycling, 178*, 106028.

Wang, Z., Su, B., Xie, R., & Long, H. (2018). China's aggregate embodied CO_2 emission intensity from 2007 to 2012: a multi-region multiplicative structural decomposition analysis. *Energy Economics, 85*, 104568.

Wu, H., Zhong, R., Wang, Z., Qu, Y., Yang, X., & Hao, Y. (2024). How does industrial intellectualization affect energy intensity? Evidence from China. *The Energy Journal, 45*(2), 27–48.

Yan, J., Zhao, T., & Kang, J. (2016). Sensitivity analysis of technology and supply change for CO_2 emission intensity of energy-intensive industries based on input–output model. *Applied Energy, 171*, 456–467.

Yuan, Q., Wang, Q., & Zhang, M. (2024a). Tracing changes in manufacturing-related carbon emissions: A structural decomposition analysis from the perspective of China. *Structural Change and Economic Dynamics, 71*, 568–581.

Yuan, R., Ma, T., & Ge, Y. (2024b). An assessment of the carbon emissions of China's ICT system from the demand and supply perspectives. *Sustainable Production and Consumption, 47*, 289–305.

Yuan, R., & Zhao, T. (2016). Changes in CO_2 emissions from China's energy-intensive industries: A subsystem input–output decomposition analysis. *Journal of Cleaner Production, 117*, 98–109.

Zhang, G., & Liu, M. (2014). The changes of carbon emission in China's industrial sectors from 2002 to 2010: A structural decomposition analysis and input-output subsystem. *Discrete Dynamics in Nature and Society, 2014*(5), 677–685.

Zhang, W., Zhang, T., Wang, S., & Li, H. (2023). CO_2 emission spillover effects in the digital transformation of China's manufacturing industry and its inter-industry differences. *Energy Reports, 10*, 520–534.

Zhang, Y. (2010). Supply-side structural effect on carbon emissions in China. *Energy Economics, 32*(1), 186–193.

Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.