RESEARCH ARTICLE



Exploring key sectors of CO₂ emissions and driving factors to spatiotemporal evolution in China from multiple perspectives

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Received: 9 January 2022 / Accepted: 21 September 2022 / Published online: 11 October 2022 © The Author(s), under exclusive licence to Springer-Verlag GmbH Germany, part of Springer Nature 2022

Abstract

Identifying CO_2 emission from different perspectives is necessary for developing the effective mitigation policies for China. Previous studies mainly focus on exploring important sectors from production and consumption sides, while the perspective of betweenness has been neglected. For narrowing the gap, a new perspective for accounting the critical transmission sectors is discussed. In this study, we calculated and compared the CO_2 emissions of production-based, consumption-based, and betweenness-based from 2012 to 2017 based on the multi-regional input–output (MRIO) model. A structural decomposition analysis (SDA) is conducted to uncover the driving forces of CO_2 emissions change from three accounting principles. The Findings are as follows: (1) the heavy industry sector (559.26 Mt) in Shandong and Jiangsu (471.97 Mt), Power in Guangdong (83.77 Mt) and Beijing (199.24 Mt), Equipment in Jiangsu (213.88 Mt) are identified as the key transmission sectors; (2) the emission intensity effect and the final demand product structure effect contribute to CO_2 emission decrease in China, which are largely offset by the structure effect of final demand source and the final demand scale effect. Based on this, we propose some typical policy implications, such as paying close attention to the production efficiency of the key transmission sectors, optimizing the intermediate product input structure and increasing investment in the technology level, and then reducing the intensity of carbon emission.

Keywords CO_2 emissions \cdot China \cdot Multi-regional input-output model \cdot Structural decomposition analysis \cdot Critical transmission sectors

Introduction

Climate change has produced significant adverse impacts on ecological, social, and economic activities. For example, unexpected outcomes from extreme weather, such as the 2021 winter blackout in Texas and broad floods in China and Europe, have brought hundreds of millions of economic

Responsible Editor: V.V.S.S. Sarma

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losses (Chen et al. 2021). Climate change mitigation would contribute to sustainable human living economic and environment development (Li et al. 2019; Wang et al. 2021). CO_2 emissions, inevitably generating from anthrophonic fossil fuel combustion, are widely regarded as the main driving factor to ongoing climate change (Gao et al. 2021; Shan et al. 2021). Therefore, carbon mitigation has become a worldwide problem for global sustainable development, and all countries need to make joint efforts to tackle with it (Ma et al. 2019; Chen et al. 2021). China, as the largest CO_2 emitter, produces about 24% of global CO_2 emissions (Li et al. 2021), and its leading advocacy as well as firm and targeted carbon mitigation action is the key to achieve global carbon reduction targets and even sustainable development target (Lv et al. 2021).

To fulfill the climate targets of carbon peak around 2030 and carbon neutrality in 2060, the Chinese government has developed a wide range of administrative policies, market mechanisms, and technological measures to mitigate the increasing CO_2 emissions (Yang et al. 2019; Li et al. 2020).

Considering the large differences in socioeconomic development, energy resource endowment, and CO₂ emissions in China, it is difficult to maintain sustainable growth of economic output, poverty reduction, and common prosperity while taking the unified policies and measures to reduce the CO₂ emissions among regions or sectors (Lee and Erickson 2017; Mak et al. 2021). At the same time, the driving factors of CO₂ emission are also different, for example, the economic development factor has a positive role in promoting CO₂ emission in most different sectors; however, the carbon emission intensity and energy intensity show the different levels of technology and also present the different influence on the different province and different sector, for the economically developed provinces, the carbon emission intensity factor will exert the negative influence on the increasing CO₂ emissions and for the economically backward areas, it will have the positive effect of promoting CO₂ emissions. Only we comprehensively understand the different driving factors of the CO_2 emissions, can government develop the effect policies for curbing the increasing of CO₂ emissions. So, fully exploring the temporal and spatial evaluation characteristics of economic development structure and CO₂ emissions of different provinces or regions is the base to resolve the trade-offs of shared socioeconomic sustainability and CO_2 emission reduction (Li et al. 2021).

Economic sectors are the cell or nodes of socioeconomic system, and play a vital role in sustaining sustainable human living (Wang and Lin 2020; Du et al. 2021). As the production center of commodities, economic sectors consume large amounts of energy resources and meanwhile generate CO_2 emissions (Pps A et al. 2020). The differences of CO_2 emissions in provinces or sectors are extremely large in China (Yang et al. 2018). Therefore, identifying the major sectors and corresponding driving factors to the increase in CO_2 emissions is especially basis and critical for China to design targeted mitigation measures from both regional and sectoral perspectives.

Accordingly, this study aims at identifying the crucial transmitting sectors of the emissions from the perspective of provincial level by using the betweenness-based method, then compares the key sectors of CO₂ emissions with both production- and consumption-based methods. The analysis of this study would help to provide insightful implications for sectoral mitigation measures because targeted measures for key transmission sectors not only contribute to carbon reduction of the sector itself but could greatly affect the output and emissions of upstream and downstream sectors. Also, we present CO₂ emissions evolution characteristics of different sectors from 2012 to 2017 by using environmental improved multi-regional input-output model (EEIO model). Besides, understanding the variations of sectoral CO₂ emissions and the underlying driving factors also provides important policy implications for sectoral mitigation. Therefore,

a structural decomposition analysis (SDA) was employed by this paper to explore the influencing factors for regional CO_2 emissions. The results of this study could provide data support and targeted mitigation polices for achieving China's carbon emissions peak and carbon neutrality targets from the sectoral level.

In what follows, Sect. 2 shows a literature review. In Sect. 3, we discuss the method employed involving the use of multi-regional input–output model (MRIO) and structural decomposition analysis (SDA). The data sources are also described, while the results and discussion are displayed in the Sect. 4. Section 5 lists our main findings and discusses on the policy implications.

Literature review

The sector-specific policies are important to control CO₂ emissions and relief climate change; previous studies attempt to explore key sectors that emit large amount of CO₂ emissions from the perspectives of production and consumption and compare the CO₂ emissions from the two methods (Schmidt et al. 2019; Jia et al. 2019). However, existing studies mainly have two research limitations (Yang et al. 2019). First, they analyze economic output and CO_2 emissions in terms of the beginning or the end of supply chain path. For example, consumption-based model reflects the simple relationship and behavior decision of final consumers, such as households, government, and capital formation, from demand-side (Wen et al. 2020; Wu et al. 2020). Production-based accounting method can examine direct CO₂ emission pressure from production process, and only quantify the efficiency of energy use and calculate the CO₂ emissions from production-side (Liu et al. 2019).

Except for the production and final consumption points, there are also existing some important process, such as intermediate transmission, that plays significant role in product supply chain (Liang et al. 2016). These links may not produce large CO_2 emission pressure, but can transmit potentially many emissions pressures in the economic-social system. It represents that huge amount of CO₂ emissions pressure passing through these transmission sectors while in the process of reproduction in supply chain paths (Liang et al. 2016; Li et al. 2021). Thus, it also should be called the key sectors of CO_2 emissions from the betweennessside (Yang et al. 2019). However, existing methods have not considered the economic activities from the perspective of intermediate transmission (Wen and Wang 2019). Second, most studies related were mainly conducted to explore important sectors of CO2 emissions at the provincial or sectoral level, and to investigate the relationship between CO₂ emission pressure and final consumption drivers or initial production drivers. More importantly, these researches failed to consider the spatial heterogeneity from the perspective of provinces or sectors within China. In other words, existing studies have limitations of fully quantifying the spatial betweenness-side CO_2 emissions of supply chains in China, especially the latest changes of these CO_2 emissions.

To address these two shortcomings, a betweenness-based accounting model is employed to sectoral analysis as transmitting centers in the supply chains (Liang et al. 2016). Betweenness-based method, originated from the network analysis, is a popular tool for quantifying the betweenness sectors by calculating supply chain paths (Yang et al. 2019; Li et al. 2021). It also innovates mitigation methods for identifying the key sectors of CO₂ emissions from traditional methods (Liang et al. 2015). Although there exist some studies on identifying the key transmission sectors by using the betweenness model for mitigating CO₂ emissions, it is a pity that they are mainly from a macro-level such as global, national, or single regional CO₂ emissions (Li et al. 2021). So far, the research and application of these important betweenness sectors of CO₂ emissions at the trans-regional or -province levels are also lacking. For example, Liang et al. (2016) adopts the betweenness model to explore the highbetweenness sectors of China's 135 sectors for mitigating CO_2 emissions. Yang et al. (2019) calculates the important transmitting sectors of energy-water-carbon nexus pressures in Shanghai and found that the chemical sector is the critical sector from the betweenness side. The later paid attention to identifying the crucial transmission centers from provinciallevel using this method, while without considering the heterogeneity of different provinces or cities (Li et al. 2021). Within considering the above limitation, how to curb CO_2 provincial emissions from betweenness-side is urgent to explore in line with China's carbon neutrality target.

The policymakers and researchers have paid more attention on the rapidly growth of emissions under the carbon neutrality target (Du et al. 2021; Ma et al. 2021). Meanwhile, an increasing number of studies has been used to identify the influencing factors of CO₂ emissions change by using the index decomposition analysis (IDA) (Li et al. 2017; Li et al. 2019), and structural decomposition analysis (SDA) (Silalertruksa et al. 2018). It is worthy that SDA model, taking a complete input-output table as database, is usually employed for analyzing the changes of direct or embodied energy use and emissions at national and regional scale research (Guo et al.; Cai et al. 2020; Wei et al. 2021), and it has more advantages in flexibility for uncovering the potential factors of CO₂ emissions changes. Existing studies have adopted SDA model to explore the contributing factors, such as CO₂ intensity, economic structure, and production structure, for affecting the differences of CO₂ emissions in China from two perspectives, including production side and consumption side (Peng et al. 2015; Wu et al. 2020). For example, Cai et al. (2020) applied SDA model, based on input–output tables, to assess socioeconomic influencing factors of China's carbon footprint from 2009 to 2016 and found that the export effect played a key role in curbing the carbon emissions. However, the studies that focused on CO_2 emissions from the perspective of betweenness side and explore its factors resulting in their changes at sectoral level are few (Wu et al. 2020).

Compared with existing studies, this study has made the contributions as follows: (1) We explore the critical sectors of CO₂ emissions based the different calculating methods at the provincial-sector level, and compare the results in a new full perspective of production-side, consumption-side, and betweenness-side. The analysis provides fully understanding of targeted sector to mitigate emissions with integrated considering regional and sectoral joint development as well as the size of CO_2 emissions in line with carbon neutrality targets. (2) Existing studies are conducted for a specific year of 2012, while this study extends the research time to 2017 from a temporal perspective, and could grasp the dynamic changes of sectoral CO₂ emissions to draw more accurate findings. (3) Regarding the growth trends of CO_2 emissions by using the I-O tables from 2012 to 2017, we explore the influencing factor behind the changes of CO₂ emissions in China from different perspectives based on the SDA model, including production, consumption, and betweenness sides. These findings could provide references for policymakers to design targeted policy to achieve carbon mitigation targets. Moreover, the analytical framework could be applied to sectoral CO₂ emission management analysis at provincial or city level in other developing countries, such as BRICS countries.

Methods and data sources

Methods

Environmental input-output analysis

Environmental input–output model relies on the traditional input–output analysis, which was proposed by the famous economist Wassily W. Leontief (Leontief, 1936) and was subsequently widely used in different fields, such as energy, CO_2 emissions, and environment; in addition, all the calculation results in this study are obtained from the 2018 version of MATLAB software. The basic equation of Leontief input–output model is

$$\mathbf{x} = A\mathbf{x} + \mathbf{f} = L\mathbf{f} \tag{1}$$

where vector \mathbf{x} indicates total outputs, matrix \mathbf{A} denotes technical coefficient, vector \mathbf{f} is final demand, and matrix \mathbf{L}

is the Leontief inverse. Equation (1) represents the dependence of total outputs on final demand.

The direct consumption coefficient matrix, technical coefficient matrix, is represented by **A**, of which an element is defined by a_{ii} .

$$a_{ij} = \frac{Z_{ij}}{X_j} (i = 1, 2, 3..., n; j = 1, 2, 3..., n)$$
(2)

where \mathbf{Z}_{ij} is a matrix that represents the number of intermediate products sold by sector *i* to sector *j*, and the column vector \mathbf{X}_j indicates the total output of economic system. Furthermore, the basic equation of Leontief input–output model was been expanded into the environmental input–output model:

$$d_j^e = \frac{E_j}{X_j} (j = 1, 2, 3...n)$$
(3)

where, d_j^e is a diagonal matrix that indicates the carbon intensity, which describes the technical level of economy, of each sector in all provinces. E_j indicates the CO₂ emissions of production in sector *j*.

According to the above conclusion, we calculated the results of this study from production-based CO_2 emission and consumption-based CO_2 emission perspectives:

Production-based CO_2 emission is mainly described using the relationship for carbon intensity and output of sectors, and consumption-based CO_2 emission is mainly described using the relationship for final demand of sectors and indirect upstream CO_2 emission. They can be calculated by the Eqs. (4) and (5):

$$p_j = d_j^e x_j \tag{4}$$

$$c_{j} = d_{j}^{e} (I - A)^{-1} y_{j}$$
(5)

where in the Eq. (4), **I** is an identify matrix $(n \times n)$; accordingly the inverse matrix, $(I - A)^{-1}$, is the Leontief inverse often represented by **L**.

Structural path analysis

Structural path analysis (SPA) unravels the Leontief inverse using Taylor expansion, which is based on input–output model, the detailed equation as the following:

$$L = (I - A)^{-1} = I + A + A^{2} + A^{3} + \cdots$$
(6)

where all production layers are named as matrix A and it can extract each supply chain path (Skelton et al. 2011; Yang et al. 2019). Each upstream production layer always inputs the production of intermediate material into the downstream production layers for producing, and production flows on supply chain path always pass from higher-power layers to lower-power layers (Skelton et al. 2011).

Appling the Taylor expansion to Eq. (5) gives:

$$e = d(I + A + A^{2} + A^{3} + \dots)y = dy + dAy + dA^{2}y + \dots$$
(7)

where, e indicates the CO₂ emission pressure, and the righthand side denotes CO₂ emission generated by each production layers (PL) under the final demand (Jia et al. 2019). In more detailed, dy indicates the direct emission pressure of sector in PL⁰.

We should define the weight in the network analysis. Suppose that the emission starts from sector *s*, goes through *r* sectors $(k_1, k_2...k_r)$, and ends at sector *t* in a complete supply chain. The weight is defined as Eq. (8):

$$w(s,t|k_1,k_2,...,k_r) = d_s a_{sk_1} \alpha_{sk_2} ... a_{k_r t} Y_t$$
(8)

where, d_s indicate the direct intensity of CO₂ in beginning sector s, $a_{sk_1}\alpha_{sk_2}...a_{k,t}$ are technical coefficients.

Further, the betweenness centrality of sector i is as following:

$$b_{i} = \sum_{s=1}^{n} \sum_{t=1}^{n} \sum_{k=1}^{\infty} \left(t_{k} d_{s} a_{sk_{1}} a_{sk_{2}} \cdots a_{k_{r}t} Y_{t} \right)$$
(9)

Betweenness-based mechanism in the supply chain

The definition of betweenness originated from network theory (Newman 2010; Li et al. 2021), which indicates the total of flow passing through a node in network. In general, the structural path analysis (SPA) is employed in betweenness centrality for exploring the key transmission sectors that have a significant CO₂ emission pressure flows through the supply chain (Yang et al. 2019), which are often overlooked when develops reduction strategies for CO₂ emission pressures (Li et al. 2021). Similarly, we extended this network theory to the provincial trade network with a multi-regional input–output structure, where the province-sectors are usually regarded nodes and the input flows among them are regarded as directed links. Table 1 describes the detailed information of CO₂ emissions from different sectors. Existing research does not take sectors B and D into carefully

 Table 1 Comparing three methods based on the supply chain (Liang et al. 2016)

Methods	Sector A	Sector B	Sector C	Sector D	Sector E
Production side	e _a		e _c		
Consumption side					$e_a + e_c$
Betweenness side		<i>e</i> _a	e _a	$e_a + e_c$	

consideration. However, if the production efficiency of sectors B and D is improved, it might help curb CO_2 emissions through reducing the inputs of sectors A and C.

According to Jia et al. (2019), the betweenness centrality of sector *i* is quantified by the following:

$$\begin{split} b_{i}(l_{1},l_{2}) &= \sum_{1 \leq k_{1},\dots,k_{i_{1}} \leq n} \sum_{1 \leq j_{1},\dots,j_{i_{2}} \leq n} (d_{k_{1}}a_{k_{1}k_{2}}...a_{k_{i_{1}}i}a_{j_{1}}...a_{j_{i_{2}}-l_{j_{i_{2}}}}Y_{j_{i_{2}}}) \\ &= \sum_{1 \leq k_{1},\dots,k_{i_{1}} \leq n} d_{k_{1}}a_{k_{1}}a_{k_{2}}...a_{k_{i_{1}}i}\sum_{1 \leq j_{1},\dots,j_{i_{2}} \leq n} a_{ij_{1}}...a_{j_{i_{2}}-l_{j_{i_{2}}}}Y_{j_{i_{2}}} \\ &= (dA^{l_{1}})_{i}(A^{l_{2}}Y)_{i} \\ &= (dA^{l_{1}}J_{i}A^{l_{2}}Y) \end{split}$$
(10)

where $b_i(l_1, l_2)$ represents the betweenness centrality of sector *i*, in which the upstream sectors is counted as l_1 and downstream sectors is counted as l_2 ; $Y_{j_{l_2}}$ denotes the final demand from sector j_{l_2} ; and J_i is a $(n \times n)$ matrix with $(i \times i)^{th}$, which its element is 1 and all the other elements being 0.

Defining $T = LA = AL = A + A^2 + A^3 + ...,$ Eq. (10) can be written as follows:

$$dA^{l_1}J_iA^{l_2}Y = dTJ_iTY \tag{11}$$

where T denotes the full consumption coefficient matrix.

Structural decomposition analysis

Structural decomposition analysis (SDA) is, a famous method, usually used to calculate the related contributions of different influencing factors to the changes and evaluations of CO_2 emissions (Jia et al. 2018). Therefore, we explore the relative drivers of contribution for the changes of CO_2 emissions by using the SDA model from the different perspectives (e.g., production, consumption and betweenness), which could provide effective policy recommendations for policymakers.

In the SDA model, the (Y^r), final demand vector, shows the meaning of the final demand of province *r*. Denoting $Y^r = (P^r \# S^r) V^r$. Here, # indicates the element-wise matrix multiplication, P^r vector is formed by stacking 30 column vectors, which is consisted by the same θ , where the vector θ are described by the share of the final goods, making P^r to represent the final demand structure of province *r*. S^r is described by stacking 30 column vectors, which is consisted by the different η^r , describing the proportion of the final products supported by province r to province m. Therefore, S^r indicates the provincial source structure of final demand volume of province r and scalar V^r indicates the total final demand volume of 30 provinces. The detailed equation based on the consumption as following:

$$C^r = D^r L^r (P^r S^r) V^r \tag{12}$$

According to Eq. (11), from time t-1 to t, changes in CO₂ emissions from consumption side can be expressed as follows:

$$\begin{aligned} \Delta C &= D_{t}^{r} L_{t}^{r} (P_{t}^{r} \# S_{t}^{r}) V_{t}^{r} - D_{t-1}^{r} L_{t-1}^{r} (P_{t-1}^{r} \# S_{t-1}^{r}) V_{t-1}^{r} \\ &= \Delta D^{r} L_{t}^{r} (P_{t}^{r} \# S_{t}^{r}) V_{t}^{r} + D_{t-1}^{r} \Delta L^{r} (P_{t}^{r} \# S_{t}^{r}) V_{t}^{r} + D_{t-1}^{r} L_{t-1}^{r} (\Delta P^{r} \# S_{t}^{r}) V_{t}^{r} \\ &+ D_{t-1}^{r} L_{t-1}^{r} (P_{t-1}^{r} \# \Delta S^{r}) V_{t}^{r} + D_{t-1}^{r} L_{t-1}^{r} (P_{t-1}^{r} \# S_{t-1}^{r}) \Delta V^{r} \\ &= C (\Delta D^{r}) + C (\Delta L^{r}) + C (\Delta P^{r}) + C (\Delta S^{r}) + C (\Delta V^{r}) \end{aligned}$$
(13)

 Δ indicates the changes of each factor, and according to the Eq. (12), the changes in the CO₂ emissions from the consumption perspective can be decomposed into five parts: $C(\Delta D^r)$ represents CO₂ emission intensity, reflecting the technological level, of different sectors in each province, $C(\Delta L^{r})$ represents structure effect of intermediate product input in each province, $C(\Delta P^r)$ represents the final demand product structure effect in each province, $C(\Delta S^r)$ indicates the structure effect of final demand source in each province, $C(\Delta V^r)$ indicates the final demand scale effect in each province, the detailed information as shown in the Table 2. In addition, the Eq. (13) is a complete decomposition method with no residual terms, but it is not the only way of decomposition. According the SDA model, different decomposition forms get the different values, the better processing method is to use the "two polar decomposition average" (Peng et al. 2015). In this study, the two polar decomposition form is employed in this paper to calculate the relatively results. The detailed equation as following:

$$\begin{split} \Delta C &= \left\{ (\frac{1}{2}) \left[\Delta D^r L_t^r (P_t^r \# S_t^r) V_t^r + \Delta D^r L_{t-1}^r (P_{t-1}^r \# S_{t-1}^r) V_{t-1}^r \right] \right\} \\ &+ \left\{ (\frac{1}{2}) \left[D_{t-1}^r \Delta L^r (P_t^r \# S_t^r) V_t^r + D_t^r \Delta L^r (P_{t-1}^r \# S_{t-1}^r) V_{t-1}^r \right] \right\} \\ &+ \left\{ (\frac{1}{2}) \left[D_{t-1}^r L_{t-1}^r (\Delta P^r \# S_t^r) V_t^r + D_t^r L_t^r (\Delta P^r \# S_{t-1}^r) V_{t-1}^r \right] \right\} \\ &+ \left\{ (\frac{1}{2}) \left[D_{t-1}^r L_{t-1}^r (P_{t-1}^r \# \Delta S^r) V_t^r + D_t^r L_t^r (P_t^r \# \Delta S^r) V_{t-1}^r \right] \right\} \\ &+ \left\{ (\frac{1}{2}) \left[D_{t-1}^r L_{t-1}^r (P_{t-1}^r \# S_{t-1}^r) \Delta V^r + D_t^r L_t^r (P_t^r \# S_t^r) \Delta V^r \right] \right\} \end{split}$$

$$(14)$$

From the perspectives of production side and betweenness side, we can also measurement emissions based on Eqs. (11)-(14).

Table 2The structuraldecomposition terms of changesin consumption-based	Factors	Definition	
	$C(\Delta D^r)$	Represents CO ₂ emission intensity effect of the production sector in each province	
	$C(\Delta L^r)$	Represents structure effect of intermediate product input in each province	
	$C(\Delta P^r)$	Represents the final demand product structure effect in each province	
	$C(\Delta S^r)$	Indicates the structure effect of final demand source in each province	
	$C(\Delta V^r)$	Indicates the final demand scale effect in each province	

Data sources

This study relates two kinds of data. One is the latest published data of the national multi-regional input-output table, and the other is the emission inventories for 30 provinces. The 2012, 2015, and 2017 national MRIO tables and CO₂ emissions data within 30 provinces are obtained from the China Emission Account and Datasets (CEADs) (Li et al. 2021). In addition, since the implementation of the Belt and Road policy, it has a great impact on China's economy after 2015, and further affected its value chain and CO₂ emissions of China in 2017; thus, the time nodes of 2015 and 2017 are also important. The national MRIO tables have the difference of sectors and classified the unified sectors with the condition of analyzing. For considering our research objectives, we have extracted the major industrial sectors and selected the large sectors for detailed analyzing. In addition, many industrial sectors have generated small CO₂ emissions and would increase the calculation difficulty for our model; thus, we merged the national MRIO table and emission inventories into the same 10 economic sectors (Appendix Table 1). Figure 1 illustrates the overall model framework of the research process.

Results and discussion

Critical transmission sectors

In this study, the critical transmission sectors are explored based on the multi-regional input–output model, which can provide a typical mitigation measurement in 30 provinces to better achieve the carbon neutrality target by 2060. Figure 2 describes the results of CO_2 emissions for10 important sectors that are calculated by the betweenness-based method across 30 provinces in 2012 (a), 2015 (b), and 2017 (c). For convenient presenting the results, we replaced the names of the 30 provinces with the letter R (as shown in Appendix Table 2). The lateral axis shows the 10 sectors in 30 provinces, and the vertical axis describes the CO_2 emissions from the perspective of betweenness.

From the temporal perspective, we can conclude that the critical sectors of CO_2 emissions are keeping the same condition, for example, heavy industry sector in Shandong province has transmitted the highest CO_2 emissions, which is the largest betweenness sector in each province in 2012 (985.36 Mt), 2015 (934.27 Mt), and 2017 (559.26 Mt), respectively, and next is the heavy industry sector in Henan province

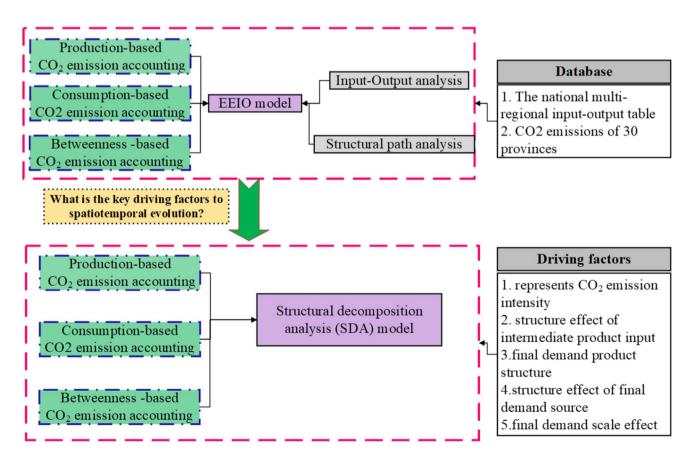


Fig. 1 Overview of the model framework

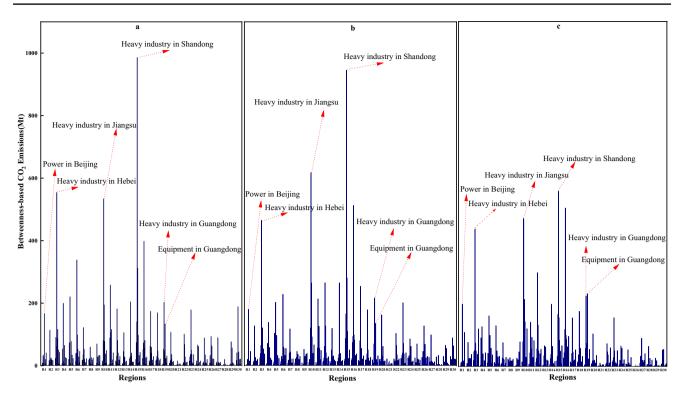


Fig. 2 The embodied CO₂ emission of betweenness-based of the 10-sector of 30 provinces in China in 2012 (a), 2015 (b), and 2017 (c)

(transmitting the embodied CO₂ emissions for 398.23 Mt in 2012, 512.71 Mt in 2015, 505.33 Mt in 2017) and heavy industry sector in Jiangsu province (transmitting the embodied CO₂ emissions for 533.89 Mt in 2012, 617.53 Mt in 2015, and 471.97 Mt in 2017). From the spatial perspective, we can conclude that the critical sectors of CO₂ emissions are showing the different conditions, for the economically developed coastal areas, the sectors of power, service, and equipment are the mainly critical sectors of CO₂ emissions, for example, for the Beijing city, the power sector (199.24 Mt) is the highest transmitting the embodied CO₂ emissions in 2017. However, for the rich mineral resources areas, the sectors of heavy industry and mining are mainly critical sectors of CO₂ emissions, for example, the Hebei province has the affluent iron resources and Shanxi has the affluent coal resources; therefore, the mining (91.23 Mt) in Shanxi and heavy industry (438.42 Mt) in Hebei are the highest transmitting the embodied CO_2 emissions in 2017.

Here, we describe and compare CO_2 emissions of different years from temporal and spatial perspectives, showing in Fig. 3 2012 (a), 2015 (b), and 2017 (c). From the temporal perspective, the CO_2 emissions of 10 sectors in 30 provinces are showing the same changing trends in 2012, 2015, and 2017, such as the total CO_2 emission of Shandong province is the largest in the all 30 provinces and concentrated in the heavy industry sector (985.46 Mt in 2012, 934.27 Mt in 2015, and 559.26 Mt in 2017) under

the betweenness-based. From the spatial perspective, there exists a huge difference in CO₂ emissions at sectoral level, for the perspective of betweenness method, heavy industry, service, equipment, and power contributed to the most of total emissions, where transmission sectors are accounting for 77.19% of the total embodied CO₂ emissions in China. Specifically, there are existing some provinces with much transmission CO₂ emissions pressure, including Shandong province, Jiangsu province, Hebei province, and Guangdong province. From the perspective consumption-based method, the major sectors for generating CO₂ emissions are the heavy industry, power and transport, which mainly located in the Shandong province, Sichuan province, Guangdong province, and Hebei province. From the perspective of productionbase method, heavy industry, power, mining, and transport mainly account for large proportion, and the typical provinces including Hebei, Inner Mongolia, and Shandong.

Comparison of different accounting methods

We rank the CO_2 emissions of different sectors in different provinces from large to small, which can more clearly understanding the CO_2 emissions from the three accounting principles. From the ranking in 2012, 2015, and 2017 (Fig. 4), a few of sectors are laying on red diagonal line, and it also indicates that most sectors have the different ranking. We are selecting the sectors of top 50 in 2017 as

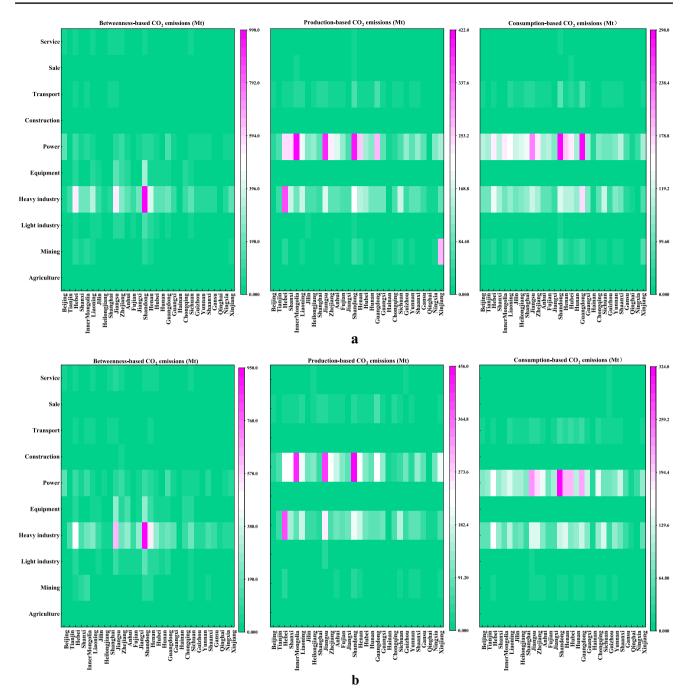


Fig. 3 The total CO₂ emission under the three methods for 30 provinces of China in 2012 (a), 2015 (b), and 2017 (c)

example, three sectors (Heavy industry in Hebei province, Heavy industry in Jiangsu province, and Light industry in Shandong province) are raking in the top 50 based on the betweenness-based model, but none ranking in the top 50 for the consumption side method, and it importantly describes the three sectors do not produce huge amount of embodied CO_2 emissions directly, which also further indicates that these sectors are usually generate the intermediate products; thus, these are less consumed by consumers; this is supported by Liang et al. (2016) and Jia et al. (2019). However, some results in this study are also different from existing studies. For example, Heavy industry in Hebei province is the largest CO_2 emissions based on the betweenness-based model, while in the study of Li et al. (2021) is the Shandong Province, which is mainly because this study merged the national MRIO table and emission inventories into the same 10 economic sectors, while in the study of Li et al. (2021) divided the emission inventories into 45

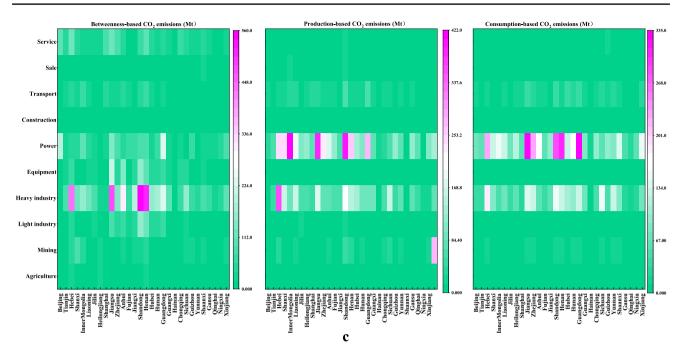


Fig. 3 (continued)

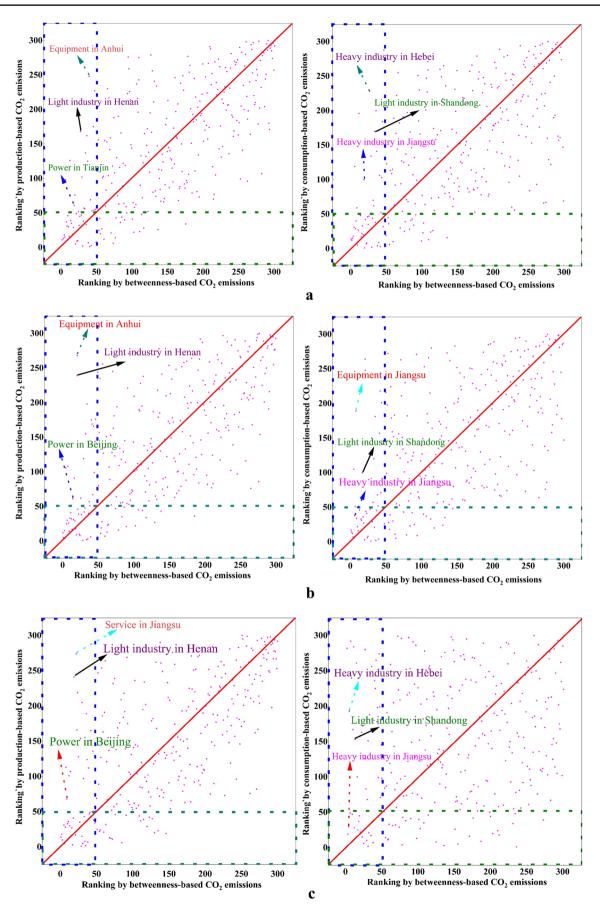
production sectors and two residential (urban and rural) sectors, and different economic sectors divisions still reveal the different raking. In addition, there also exist three sectors (Light industry in Henan province, Service in Jiangsu province, and Power in Beijing city) ranking in the top of 50 according to the betweenness-based method; however, they do not rank in the top 50 by production-based method. This means that these sectors with high betweenness but products of these sectors not generate much embodied CO_2 emissions, which further shows that these sectors have little room to reduce the CO_2 emissions under the production-based method.

We can get a conclusion from above analysis that these sectors are often ignored in polices related to mitigated the CO_2 emissions. However, these typical sectors are transferring the huge pressure of CO_2 emissions in the process of production and along with the whole supply chains. Therefore, it is vital to formulate the suitable policies for improving the produce efficiency of them sectors for reducing the need of intermediate inputs.

Furthermore, we further point out that some sectors are in the place where the blue dashed boxes and the green dashed boxes overlap, and indicates these sectors are regarded as crucial sectors of embodied CO_2 emissions from the all three methods. In order to provide a detailed comparison result, we list the CO_2 emissions of top 15 based on the three accounting methods (Table 3). The results of the Table 3 further show that some sectors should pay attention to curb the CO_2 emissions and this method exert a significant influence in quantifying the CO_2 emissions at the provincial level. It is worth noting that the betweenness-based method differs from the production-based and consumption-based methods when estimating the sectoral and provincial perspectives, for example, the Service and Light industry are not emission-intensive industries in some provinces, but they indeed contributed much for transferring the CO_2 emissions, which concludes a new visual angle to calculate the important betweenness sectors, and must not ignored in formulating emission reduction policies. Therefore, more attention to these critical transmission sectors would make a positive impact on CO_2 emission reduction and management.

Comparison with other studies

Existing accounting principles would neglect the intermediate transmission sectors, while betweenness-based method could calculate the CO₂ emissions of critical transmission sectors. This is supported by Liang et al. (2015) and Jia et al. (2019). However, some results in this study are also different with existing previous studies. It is worth noting that this study is based on the latest input–output tables in 2012, 2015, and 2017, while the most previous studies are based on 2012; therefore, we compare the calculations with previous literature in 2012. For example, in the study of Peng et al. (2015) and Qiang et al. (2020) are only calculated the embodied CO₂ emissions, they also only describe the mainly sectors of CO₂ emission, such as heavy industry, power and mining sectors; however, the equipment and service sectors are ignored. In this study, the calculation results of key



<Fig. 4 The rankings of CO_2 emissions at sectoral level under the comparison of three methods in 2012 (a), 2015 (b), and 2017 (c). We use the two-dimensional representation, horizonal axes, and vertical axes, to show the ranking of CO_2 emissions of each sector by using the betweenness-side accounting method, production-side accounting method, and consumption-based method, respectively. In addition, we pick out the sectors that rank the top of 50 under the accounting principles, and further mark these by the different colors, including blue dashed lines and green dashed lines

transmission sectors are different from the study of Li et al. (2021) that light industry is the key transmission sector. This is mainly because the scope of the sector merger is different, in our study, we combined the original 42 sectors of the I-O table into 10 sectors, while 30 sectors in the study of Li et al. (2021).

Crucial drivers of CO₂ emissions from demand, supply and betweenness sides

Changes of CO_2 emissions are affected by numbers of social and economic factors, including the improvement of technology, population explosion, adjustment of the industrial structure. To uncover the related contributions of different social and economic drivers, the changes of overall CO_2 emissions of China's 30 provinces during 2012–2017 are decomposed from production, consumption, and betweenness perspectives, showing in Fig. 5.

For the convenience and accuracy of analyzing the drivers of CO_2 emissions changes, this paper divides China's 30 provinces into four regions (as shown in Appendix Table 3), and we analyze the influencing factors from the three perspectives (production side, consumption side, and betweenness side). From the production side, we can see from the

decomposition results during the whole study period time (as shown in Fig. 5) that except the west region, the other three regions have the same situation, which show that the largest negative influencing factor of CO₂ emissions during 2012–2017 is emission intensity (ΔD), followed by the final demand product structure effect (ΔP) while the final demand scale effect (ΔV) promote the increasing in the CO₂ emissions. As the most economically developed East region with the highest CO_2 emissions, the emission intensity in East region makes the strongest negative contributions to CO₂ emissions (ΔD: 2012–2015: 189.3 Mt, 2015–2017: 335.4 Mt), followed by the Northeast region, the contribution value is - 178.9 Mt (2012-2015) and - 235.1 Mt (2015–2017), as described by the red blocks shown in Fig. 5. Among the positive factors of promoting the increasing of CO₂ emissions of China, the final demand scale effect (ΔV) acted as the most important role in four regions, with the most contribution value of 345.6 Mt in East region (2012–2015) and 554.7 Mt (2015–2017). It is worthy to noting that the factor of emission intensity has promoted the CO₂ emissions in West region, with the contribution value is 101.4 Mt (2012–2015) and 45.9 Mt (2015–2017), it mainly attributed to its relatively less developed economy and technology, of which Chongqing city is a municipality in our country, and has many universities and scientific research institutions; therefore, its technological level relatively developed than other provinces, such as Yunnan, Guizhou, and Gansu, but for the Ningxia and Xinjiang provinces, their economic and technical level are more less developed, accordingly their energy use is inefficient and emission intensity is high.

From the consumption side, from the decomposition results, we can conclude that (in Fig. 5) the influencing

Table 3 Comparison of CO_2 emissions ranking top 15 underthe three accounting methods in10 sectors 30 provinces in 2017

Ranking order	CO ₂ emissions by betweenness-based	CO ₂ emissions by consumption-based	CO ₂ emissions by production-based
Heavy industry in Shandong	1	282	14
Heavy industry in Henan	2	19	18
Heavy industry in Jiangsu	3	30	10
Heavy industry in Hebei	4	193	4
Heavy industry in Anhui	5	49	31
Power in Guangdong	6	292	5
Heavy industry in Guangdong	7	240	28
Equipment in Jiangsu	8	47	113
Power in Beijing	9	167	68
Heavy industry in Jiangxi	10	284	33
Heavy industry in Hunan	11	28	36
Light industry in Shandong	12	153	101
Heavy industry in Inner Mongolia	13	129	30
Equipment in Shandong	14	261	107
Heavy industry in Sichuan	15	100	16

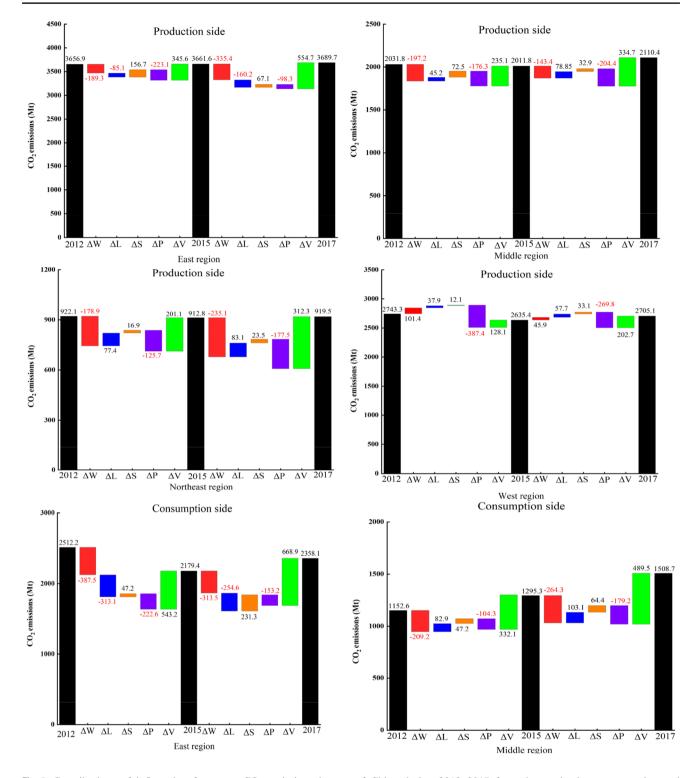
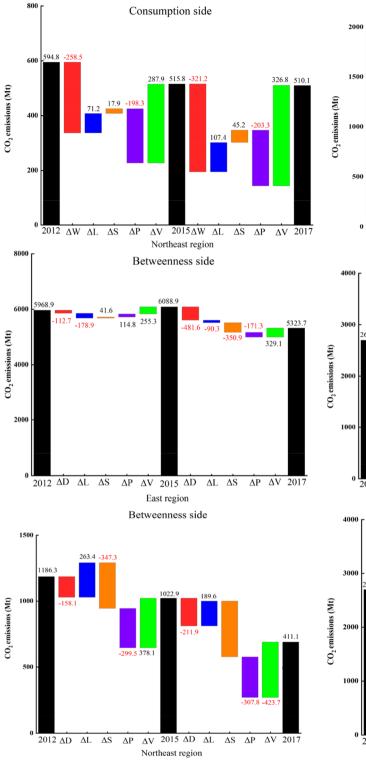


Fig.5 Contributions of influencing factors to CO_2 emission changes of China during 2012–2017 from the production, consumption and betweenness sides



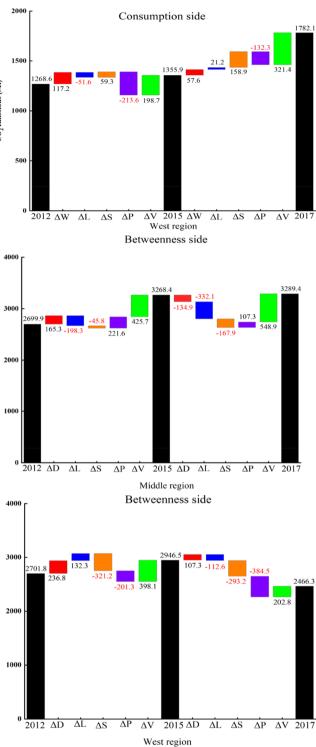


Fig. 5 (continued)

factors are showing the difference trend in the four regions, which the final demand scale effect (ΔV) and structure effect of intermediate product input (ΔL) are the main reasons for promoting the increasing of CO_2 emissions. Except the west region, the factor of emission intensity (ΔD) and the final demand product structure effect (ΔP) are playing an important role in avoiding the increasing of CO₂ emissions. Taking the East region and West regions as examples, the contribution value of the final demand scale effect (ΔV) in East and West regions reach for 1212.1 Mt and 520.3 Mt during the period of 2012–2017, respectively. Except for the West region (ΔD : 117.2 Mt: 2012–2015; 57.6 Mt: 2015–2017), the factor of emission intensity contributes the most in terms of decreasing the CO₂ emissions in the East region, the red blocks as shown in Fig. 5 (ΔD : – 387.5 Mt in 2012-2015; - 313.5 Mt in 2015-2017). The reasons for these results lie in that (1) the East region, with high economic development and energy utilization levels, its emission intensity is lower than the less developed West region, for example, the economic development and energy utilization levels of Beijing city are much more than Guangxi province; (2) the population scale of East region is larger than the West region, and needing more goods and services to support the population in East region, thus the final demand scale effect contributes the larger values in the CO₂ emissions. In addition, the structure effect of intermediate product input (ΔL) shows the negative role in East region, while shows the positive role in West region, it attributes that intermediate product input structure in economically developed East region shows the low carbon trend, the service, sale and transport sectors account for the large percent and these industries are relatively capital and technologyintensive. However, in the West region, the heavy industry and mining account for the large present (Li et al. 2017), thus generate much CO_2 emissions.

From the betweenness-side, we can conclude that (shown in Fig. 5) the four regions have the different situation and decomposition results as those obtained at the betweenness side, which shows that the emission intensity factor (ΔD) promotes the increasing of CO2 emissions in the West region and Middle region during the study period time of 2012–2015, the contribution value reaches the 236.8 Mt and 165.3 Mt. respectively. However, the factor of emission intensity inhibits the increasing of CO₂ emissions in the East region and Northeast region, while the final demand scale effect (ΔV) and the structure effect of final demand source (ΔS) promote the increasing of CO_2 emissions in four regions. As to the positive factors, the final demand scale effect is regarded as the most important role in promoting the increasing of CO₂ emissions in China, from betweenness side (comprising four regions). In the East region, the absolute contribution value of the final demand scale effect (ΔV) is 255.3 Mt (2012–2015) and 329.1 Mt (2015–2017), respectively.

Followed by the structure effect of final demand source (ΔS), with a contribution value of 84.1 Mt during 2012–2017, seen the dark yellow blocks in Fig. 5, it mainly related to the East region has a developed economy level, the income level percapita is absolutely higher than the other regions (Li et al. 2017); thus, the East region needs to consume more expenditure commodities (consumed more resource and inevitably generate more CO₂ emissions) to feed their own population.

The SDA results have revealed the influencing factors in changes of CO₂ emissions obtained from the three accounting methods and are showing different situation and decomposition results. From the decomposition results, we infer two important conclusions; on the one hand, the total carbon emission of consumption-side in developed areas is higher than that the production-side in less developed region, which further indicates that economically developed regions depend on their capital and technological advantages to import large quantities of energy-intensive and carbon-intensive products and services from economically less developed areas to avoid their local CO2 emissions and environmental damage. On the other hand, whether production-side, consumption-side or betweenness-side, its emission intensity effect and intermediate input structure effect in the economically developed area play an important role in inhibiting the changes of carbon emissions; therefore, improving the technological level must be ranked first and pay more attention to the reduction of CO₂ emissions, which further indicates that the improvement of economic level can drive the optimization and upgrading of economic structure and reduce the demand for low-level intermediate input. On the contrary, for the less developed economic region, its energy utilization level is relatively low; in other words, one unit output value is needed more energy consumption, and inevitably generating more carbon emission. In addition, we also can infer that the final demand scale effect plays a significant role in promoting the increasing of carbon emissions in all regions, because all the regions need to consume goods and services to support the development of the local economy. This further shows that economic development can provide employment and promote the urbanization process.

Conclusions and policy implications

Conclusions

This study adopts MRIO model to investigate the pivotal sectors of transferring CO_2 emissions using the betweennessbased method, and compares the results with the consumptionbased and production-based methods. Moreover, we conduct the SDA to further uncover the influencing factors of contributing to the changes of CO_2 emissions from 2012 to 2017. The main conclusions of our study are as follows:

- The findings show that, from the perspective of (1)betweenness method, heavy industry, service, equipment, and power contributed most to total emissions, which transmission sectors are accounting for 77.19% of the total CO₂ emissions through the accounting of betweenness-based method. Heavy industry sector (559.26 Mt) in Shandong province, Henan province (505.33 Mt), and Jiangsu province (471.97 Mt) are the key transmission CO_2 emissions. These sectors may not produce large emission pressure, but transmit potentially much emission pressure in the economy system. Heavy industry in Hebei and Jiangsu, and Light industry in Shandong rank the top 50 of CO₂ emissions from the betweenness-side accounting perspective, but not rank in the top 50 from the consumption-side accounting perspective. In addition, the Light industry in Henan, Service in Jiangsu, and Power in Beijing are ranking in the top 50 in terms of embodied emissions based on the betweenness-based method.
- (2)There are significant differences of the contributions of various factors among production-side, consumptionside, and betweenness-side. First, emission intensity effect shows the most important contribution to restrain the growth of CO₂ emissions from the three accounting principles, while final demand scale effect is the key driver to increase CO₂ emissions. Notably, emission intensity effect shows the positive influence on the increasing of CO_2 emissions in the less developed West region from the three perspectives. Second, final demand structure effect is the most important driver for inhabiting the growth of CO2 emissions to the production-side. The structure effect of final demand source shows the positive impact on the increase of CO₂ emissions from both consumption-side and betweennessside perspectives.

Policy implications

Many CO_2 reduction policies at the national or regional level have been formulated from the perspectives of production and consumption; however, the calculation of CO_2 emissions by the betweenness-based method is generally neglected. Thus, to develop a more comprehensive policy decision and avoid the unilateral emission reduction policies, we support the tailored mitigation policy recommendations shown as follows:

(1) Pay close attention to the improvement of utilization efficiency of the key betweenness sectors and of standards of the input in terms of environmental benefits are advocated. For example, first, material recycling and reducing waste can help reduce upstream input and weakening the sector's transmission to CO_2 emissions.

Second, local governments should formulate standards to encourage industries to improve technology, reduce waste, control procurement, and optimize production processes. In addition, strict standards should be set to govern enterprise to input the environmental-friendly intermediate inputs.

- (2)Optimize market mechanism to guide investment behavior to improve the investment of research and development and further improve the resource utilization technology to reduce the intensity of carbon emission. Emission intensity must be paid the most attention to the reduction of CO₂ emissions in the province and sector level. On the one hand, enterprises should make great efforts in improving the fuel mix through advocating the purchase and use of renewable energy and electric vehicles, reducing the new coal combustion projects, controlling the present of coal resources in the total energy consumption. On the other hand, enterprises should actively introduce advanced technology to reduce the emission per unit of product, especially for the sectors of transmitting the huge pressure of CO₂ emissions during production process in China, such as heavy industry, mining, and power sector.
- Government should promote collaborative industrial (3) layout and optimize the intermediate product production structure. As for developed east region, the intermediate product production structure shows an opposite influence on the growth of CO₂ emissions, while shows positive influence on the less developed regions. Therefore, governments of the less developed regions should encourage industrial restructuring through (1) providing preferential capital, tax, and technological policies to promote the development of high-tech industries, (2) transferring traditional energy-intensive industries to less development foreign markets, and (3) building electronic platform for industrial transfer and information sharing to balance mitigation target and production cost.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s11356-022-23247-7.

Author contribution Xianmei Liu and Caiquan Bai conceived the ideas, designed the research framework, and performed the literature research. Xianmei Liu, Rui Peng, and Song Wang performed the data collection and result calculation, and led the writing of the manuscript. Caiquan Bai led the revising of the manuscript. All authors read and approved the final manuscript.

Funding This research was supported by the National Natural Science Foundation of China (Grant Nos. 72071005; 71874119), National Social Science Foundation of China (Grant No. 19ZDA081), and Natural Science Foundation of Shandong Province (Grant No. ZR2021QG062).

Data availability The datasets used and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate Not applicable.

Consent for publication Not applicable.

Competing interests The authors declare no competing interests.

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