Frontiers in Power and Energy Systems (2024)
Clausius Scientific Press, Canada

DOI: 10.23977/fpes.2024.030103
ISSN 2516-2926 Vol. 3 Num. 1

Betweenness-Based Method to Identify Critical Provincial Carbon Transport Sectors in the Yellow River Basin and Explore Spatiotemporal Evolution Driving Factors

Ruixi Zhu

School of Management, China University of Mining and Technology, Beijing, 100091, China
z2958242159@163.com

Keywords: CO_2 Emissions, Multi-Regional Input-Output Model, Betweenness-Based Method, Yellow River Basin, Structural Decomposition Analysis

Abstract: Identifying key provincial sectors and their influencing factors is of significant importance for driving precise carbon reduction policies and achieving the "dual carbon" goals. Previous studies have typically identified key sectors either from the production and consumption sides, aiming to pinpoint those sectors directly or indirectly responsible for significant carbon emissions, while the perspective of betweenness has been neglected. This paper proposes a framework based on betweenness centrality and identifies key carbon-emitting sectors at the inter-provincial level in the Yellow River Basin for the years 2012, 2015, and 2017. The results indicate that both production-based and consumption-based approaches overlook certain crucial provincial transmission sectors, such as Inner Mongolia's coal mining and selection products and Henan's chemical product manufacturing sectors. Over the years, these sectors2 have emitted significant amounts of carbon dioxide within the supply chain. From an industry perspective, the focus on carbon emissions has gradually shifted from heavy industries such as chemical product manufacturing and metal smelting and rolling processing to light industries such as water production and supply. From the perspective of provincial departments, the chemical products manufacturing industry in Shandong, as well as the metal smelting and rolling processing industry in Shandong, Inner Mongolia, Shanxi, and Henan provinces, are considered key sectors for carbon reduction. Meanwhile, the water production and supply industries in Sichuan, Henan, Inner Mongolia, Shanxi, and Shandong provinces are regarded as critical sectors for carbon increase. Furthermore, input-output technology is the primary factor causing changes in CO_2 emissions from sectors. Building upon this foundation, we propose several policy recommendations, such as closely monitoring the production efficiency of key sectors, optimizing the structure of intermediate input, and enhancing energy utilization efficiency, thereby reducing carbon dioxide emissions.

1. Introduction

In 2022, global CO_2 emissions amounted to approximately 36.07 gigatons, marking a 1.5% increase (5.4 gigatons) compared to 2021 [1]. Furthermore, there was a notable rise in emissions compared to 2020 and 2019, with increases of 7.9% (26.4 gigatons) and 2.1% (7.3 gigatons) respectively [2]. This indicates a continuous and rapid growth in global CO_2 emissions. Faced with this alarming situation, nations worldwide are taking action to reduce carbon emissions.

Since 2007, China has surpassed the United States to become the world's largest emitter of carbon, thus drawing significant global attention to China's emission reduction plans. To address global climate change and shoulder its responsibilities as a major country, China proposed the "dual carbon" goal at the 2020 United Nations General Assembly debate, aiming to peak carbon emissions before 2030 and strive for carbon neutrality by 2060 [3].

To alleviate environmental pressure, previous studies have primarily employed two methods: one is production-based, identifying critical sectors directly generating CO_2 emissions, such as enhancing energy efficiency through technological innovations [4,5]; the other is consumption-based, pinpointing key sectors indirectly contributing to CO_2 emissions, for instance, researching sectors' sensitivity to carbon taxation to enhance its effectiveness [6], thus achieving greater carbon emissions reduction. However, both of these perspectives overlook the carbon emissions generated in the intermediate processes from primary production to final consumption. Based on this, some scholars have proposed intermediary-based methods to quantify environmental pressure, such as Liang et al. employed a betweenness method to explore industries in China where carbon emissions play a critical role [7].

However, these studies mainly focus on the macro level, such as the CO_2 emissions of individual countries [8] or single provinces [9]. So far, research and applications regarding the crucial intermediate links of CO_2 emissions across regions and provinces are relatively lacking [10]. Meanwhile, economic sectors serving as centers of commodity production consume significant amounts of energy resources and emit CO_2 [8]. The differences in CO_2 emissions among provinces or industries in the Yellow River Basin are also quite significant [11]. Therefore, it is particularly important to identify the key provincial sectors and the driving factors behind their carbon emissions to design targeted emission reduction measures.

Previous research has predominantly utilized the Structural Decomposition Analysis (SDA) method to explore factors influencing the variation of carbon emissions in Chinese cities from two perspectives: the production side (carbon emission intensity, production structure, and final demand structure) and the final demand side (rural, urban residents, government consumption, exports, and imports). For example, Wang et al. found that production structure and final demand were the main driving factors of CO2 emissions changes in Beijing from 1997 to 2010 [12]. However, there is limited research focusing on CO2 emissions from an intermediate perspective and exploring the influencing factors of its variation at the sectoral level [10].

In this study, we employed a betweenness-based framework to assess the environmental pressure exerted by each sector. Initially, by comparing the rankings of carbon dioxide emissions for 270 provincial-level sectors in 2012, 2015, and 2017, we identified crucial sectors for carbon emission transmission. Subsequently, we compared provincial-level sector rankings betweenness-based methods and production-based or consumption-based methods to demonstrate the correlation of the betweenness-based method with the two traditional approaches. Additionally, focusing on the trends of CO_2 emissions from nine provincial-level sectors from 2012 to 2017, we utilized the SDA model to explore the influencing factors of CO_2 emission changes from a betweenness perspective. Based on the research findings, supplementary decarbonization policies targeting specific provincial-level sectors in the Yellow River Basin were proposed.

The main contributions of this study are as follows: (1) The key sectors responsible for substantial carbon dioxide emissions have been identified by the betweenness-based method, providing new insights into carbon reduction. (2) The spatial-temporal evolution characteristics of key transmission links of carbon emissions in the Yellow River Basin were analyzed. (3) Specific carbon emission reduction policies at the provincial department level in the Yellow River Basin were proposed.

2. Methods and Data

2.1 Multi-Regional Input-Output Method

The MRIO (Multi-Regional Input-Output) model relies on the traditional input-output method, first introduced by Leontief in 1936 [13], and has subsequently found widespread application in the fields of energy [14] and carbon emissions [15]. Within an input-output table, the total output of society equals the sum of intermediate inputs and final demand. The equilibrium equation is:

$$\sum_{j=1}^{n} x_{ij} + Y_i = X_i \qquad i = 1,2,\dots,n \tag{1}$$

Where x_{ij} represents the intermediate products sold from sector I to sector j, Y_i denotes the final consumption of sector i, and X_i represents the total output of sector i. The direct consumption coefficient a_{ij} is defined as follows:

$$a_{ij} = \frac{x_{ij}}{X_j}(i,j = 1,2,\dots,n) \tag{2}$$

Substituting expression (2) into expression (1), we obtain:

$$\sum_{j=1}^{n} a_{ij}X_j + Y_i = X_i \ (i = 1,2,\dots,n) \tag{3}$$

Assuming the direct consumption coefficient matrix is denoted as A, with X and Y representing the total output column vector and final demand column vector respectively, we can derive:

$$AX + Y = X \tag{4}$$

Expanding upon formula (4), we can derive:

$$X = (\mathrm{I} - \mathrm{A})^{-1}\mathrm{Y} = \mathrm{LY} \tag{5}$$

Here, L denotes the Leontief inverse matrix, and formula (5) illustrates the dependence of total output on final demand.

The CO_2 emissions from production primarily rely on the relationship between carbon emission intensity E and total output X for each sector, whereas the CO_2 emissions from consumption are predominantly described by the relationship between sectoral final demand Y and indirect CO_2 emissions. These can be respectively represented by formulas (6) and (7):

$$\mathrm{C} = \mathrm{E}X \tag{6}$$

$$\mathbf{C} = \mathbf{E}(\mathbf{I} - \mathbf{A})^{-\mathbf{1}}\mathbf{Y} \tag{7}$$

2.2 Betweenness-based Method

The concept of "betweenness" was originally introduced by scholar Linton Freeman in 1977 [16] in the field of social network analysis. Initially widely applied in the study of social networks, it was later extended to identify key transmission sectors generating substantial environmental pressures [7]. The concept of betweenness measures the importance of sectors as transmission hubs within the economy, which can further guide the formulation of environmental pressure mitigation strategies at various sectoral levels. In this study, provincial-level departments are typically regarded as nodes, and the inputs between departments are considered as connections. From Figure 1, it can be seen that both the production-based and consumption-based methods have failed to adequately consider sectors B and D. However, the betweenness-based method identifies sectors B and D as critical. Therefore, the betweenness-based method offers a fresh perspective for strategic planning.

Methods	SectorA	SectorB	SectorC	SectorD	SectorE
Production-based	Ea		Ec		
Consumption-based					Ea+Ec
Betweenness-based		Ea	Ea	Ea+Ec	

SectorA → SectorB → SectorC → SectorD → SectorE → Final Demand

Figure 1: Example supply chain to explain the betweenness-based method

To evaluate the betweenness of sectors, we expand the input-output model formula (4) by the Taylor series. The detailed equations are as follows:

$$C = E(\mathrm{I} - \mathrm{A})^{-1}Y = E(I + A + A^2 + A^3 + \cdots)Y = EY + EAY + EA^2Y + EA^3Y + \cdots \quad (8)$$

The terms on the right side represent the carbon emission pressure generated by each production layer (PL) under the final demand-pull. EIY represents the direct carbon emissions from the zeroth-level production layer driven by final demand, while ($EAY + EA^2Y + \ldots$) represents the indirect carbon emissions from the first-level production layer and beyond, all driven by final demand. Assuming a supply chain path starts from sector s, passes through r sectors (denoted as k_1, k_2,..., k_r), and eventually reaches sector t, the weight of the supply chain path can be represented as follows:

$$w(s,t|k_1,k_2,\cdots,k_r) = E_s a_{sk_1} a_{k_1k_2} \cdots a_{k_{r-1}k_r} a_{k_rt} Y_t \quad (9)$$

Where Es represents the carbon emission intensity of sector s; Y_t denotes the final demand of sector t; and $a_{sk_1} a_{k_1k_2} \cdots a_{k_{r-1}k_r} a_{k_rt}$ represent the direct consumption coefficients between different sectors. The betweenness centrality of sector i is calculated as follows:

$$b_i = \sum_{s=1}^{n} \sum_{t=1}^{n} \sum_{r=1}^{\infty} q_r \times w(s,t|k_1,k_2,\cdots,k_r) \quad (10)$$

The variable q_r represents the frequency of sector i appearing in the supply chain paths. The higher the frequency of sector i appearing in the supply chain paths, the higher its betweenness centrality value, indicating that sector i is a high-carbon sector located at the center of the supply chain.

Assuming that sector i has l_1 upstream sectors and l_2 downstream sectors in the supply chain, the total weight of all supply chains passing through sector I can be expressed as follows:

$$b_i(l_1, l_2) = \sum_{1\le k_1,\cdots,k_{l_1}\le n} \sum_{1\le j_1,\cdots,j_{l_2}\le n} \left(E_{k_1} a_{k_1k_2} \cdots a_{k_{l_1}i} a_{ij_1} \cdots a_{j_{l_2-1}j_{l_2}} Y'_{j_{l_2}}\right)$$
$$= \left(\sum_{1\le k_1,\cdots,k_{l_1}\le n} e_{k_1} a_{k_1k_2} \cdots a_{k_{l_1}i}\right)\left(\sum_{1\le j_1,\cdots,j_{l_2}\le n} a_{ij_1} \cdots a_{j_{l_2-1}j_{l_2}} Y'_{j_{l_2}}\right) \quad (11)$$
$$= EA'^{l_1} J_i A'^{l_2} \mathrm{Y}$$

Where Ji is a n $\times$ n matrix, with diagonal elements (i, i) equal to 1 and all other elements to 0.

Let $\mathrm{T} = \mathrm{LA}' = \mathrm{A}'\mathrm{L} = \mathrm{A}' + \mathrm{A}'^2 + \mathrm{A}'^3 \cdots$,T is the matrix of complete consumption coefficients. Then, the betweenness of sector i is:

$$b_i = ETJ_iTY \quad (12)$$

Let $L' = TJ_iT$, then the betweenness-based CO_2 emissions can be described to the final demand Y and the total CO_2 emissions. They can be expressed as:

$$\mathrm{C} = \mathrm{EL}'\mathrm{Y}^{\leftarrow} \quad (13)$$

2.3 Structural Decomposition Analysis

In the SDA model, the final demand vector can be decomposed into the final demand structure y_s and the total final demand y, while the total final demand can be further decomposed into the population size P and the per capita final demand y_v [10]. Therefore,

$$Y = Py_sy_v \quad (14)$$

Based on equation (13), the structural decomposition analysis model for the betweenness-based carbon emissions impact factors can be derived as follows:

$$C = EL'Py_sy_v \quad (15)$$

Consequently, the variation in betweenness-based CO_2 emissions can be represented as:

$$\Delta C = \Delta EL'y_sy_vP + E\Delta L'y_sy_vP + EL'\Delta y_sy_vP + EL'y_s\Delta y_vP + E_sE_iL'^{y_sy_v}\Delta P \quad (16)$$

$$\Delta C = f(\Delta E) + f(\Delta L') + f(\Delta y_s) + f(\Delta y_v) + f(\Delta P) \quad (17)$$

From equation (17), it can be seen that the change in carbon emissions ΔC is decomposed into five major influencing factors: population size (P), carbon intensity (E), input-output technology (L'), final demand structure (y_s), and per capita final demand (y_v).

2.4 Data Resources

This study utilizes two sets of data: input-output tables and provincial emission inventories. The MRIO tables for China in 2012, 2015, and 2017 [17] encompass 31 regions, and 42 socioeconomic sectors. Meanwhile, the emission inventory data for 30 provinces in China in 2012 [18], 2015 [18], and 2017 [19] cover 30 regions and 47 sectors (45 production sectors and 2 residential sectors).

Given the disparity between the 42 sectors in the national MRIO table and the 47 sectors in the emission inventory, we have integrated them based on the "Classification of National Economic Industries" released by the General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China in 2017, consolidating them into 30 sectors (Table 1). Furthermore, since this paper focuses only on the analysis of 9 provinces within the Yellow River Basin, it is not possible to fully disaggregate the export portion of final demand in the IO table for all 31 provinces of China. Therefore, we will directly use the export values corresponding to the 9 provinces from the IO table as the export values solely for these 9 provinces themselves.

Table 1: Sector information for betweenness-based analysis

Code	Sector category	Code	Sector category
S1	Agriculture, Forestry, Animal Husbandry and Fishery	**S16**	Manufacture of general-purpose machinery
S2	Mining and washing of coal	**S17**	Manufacture of special-purpose machinery
S3	Extraction of petroleum and natural gas	**S18**	Manufacture of transport equipment
S4	Mining and processing of metal ores	**S19**	Manufacture of electrical machinery
S5	Mining and processing of nonmetal and other ores	**S20**	Manufacture of communication equipment, computers, and other electronic equipment
S6	Food and tobacco processing	**S21**	Manufacture of measuring instruments
S7	Textile industry	**S22**	Other manufacturing
S8	Manufacture of leather, fur, feathers, and related products	**S23**	Comprehensive use of waste resources
S9	Processing of timber and furniture	**S24**	Production and distribution of electric power and heat power
S10	Manufacture of paper, printing, and articles for culture, education, and sport activity	**S25**	Production and distribution of gas
S11	Processing of petroleum, coking, processing of nuclear fuel	**S26**	Production and distribution of tap water
S12	Manufacture of chemical products	**S27**	Construction
S13	Manufacture of non-metallic mineral products	**S28**	Wholesale and retail trades
S14	Smelting and processing of metals	**S29**	Transport, storage, and postal services
S15	Manufacture of metal products	**S30**	Other services

3. Result

3.1 Betweenness-based CO2 Emissions Ranking for Provincial Sectors

The carbon emissions and ranking changes at the sector level in the Yellow River Basin of China for the years 2012, 2015, and 2017, based on the betweenness-based method, are illustrated in Figure 2. From the graphs, it can be observed that in 2012 and 2015, Shandong Manufacture of Chemical Products (ranked 1, 1), Shandong Smelting and Processing of Metals (ranked 2, 2), Henan Smelting and Processing of Metals (ranked 3, 3), Shanxi Smelting and Processing of Metals (ranked 5, 7), and Henan Manufacture of Non-metallic Mineral Products (ranked 6, 4) are identified as leading sectors by the betweenness method. Moreover, these sectors maintained their positions in the top 20 rankings according to the betweenness method in 2017. From the sector perspective, these sectors exhibit relative stability and significance, showing no significant changes over time. From the provincial perspective, these heavy industries are primarily concentrated in Shandong and Henan provinces.

However, in 2017, the betweenness-based method revealed that the top five sectors were the Production and Distribution of Tap Water in Sichuan, Henan, Inner Mongolia, and Shanxi, along with the Manufacture of Non-Metallic Mineral Products in Henan. It is noteworthy that in 2012, the betweenness centrality of Sichuan's tap water production and distribution ranked 180th in the multi-regional implicit carbon network of the Yellow River Basin. By 2015, this ranking had dropped to 197th, but by 2017, it had risen to 1st place. Simultaneously, Henan and Inner Mongolia also exhibited an overall upward trend in the ranking of tap water production and distribution, with rankings in 2012, 2015, and 2017 being 135, 124, and 2 for Henan, and 158, 165, and 3 for Inner Mongolia, respectively.

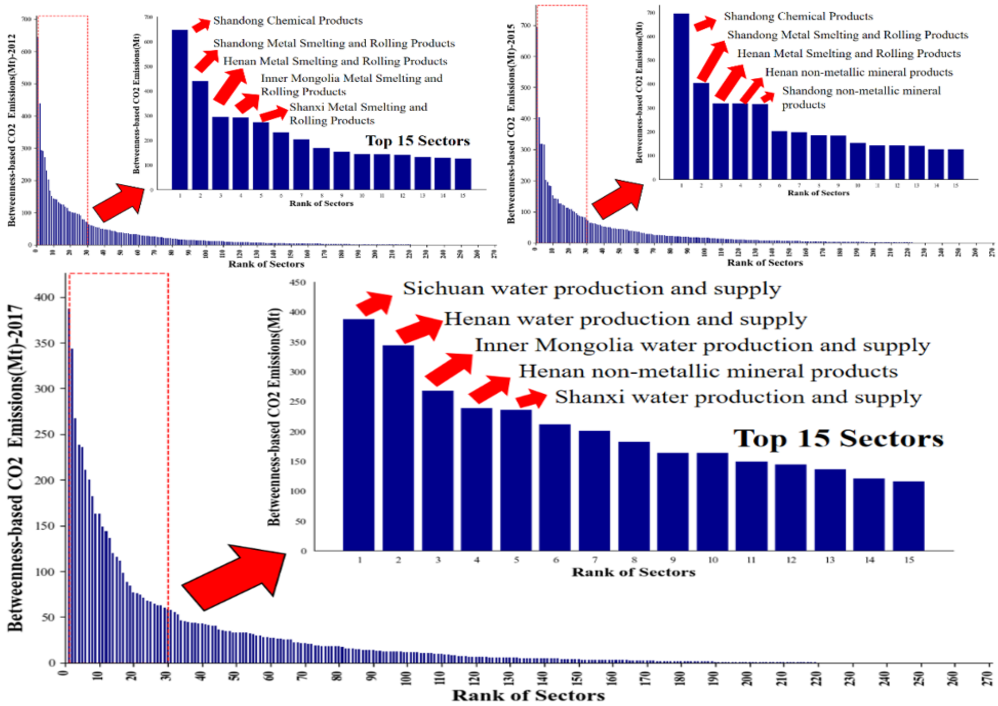

Figure 2: Betweenness-based CO2 emissions for 30 provincial sectors in 9 provinces in 2012, 2015, 2017 (a total of 270 provincial sectors)

3.2 Correlation with Production-Based and Consumption-Based Results

The Kendall correlation coefficients for city rankings between the Betweenness-based method and the production-based method or consumption-based method are presented in Table 2. In 2012, 2015, and 2017, the p-values for the Betweenness-based method and the production-based method were 6.55×10^{-21}, 8.37×10^{-51}, and2.54×10^{-26}, respectively. The p-values for the consumption-based method and Betweenness-based method were 8×10^{-6}, 2.35×10^{-28}, and 1.05×10^{-25} for the corresponding years. All these values are less than 0.01, indicating a highly significant relationship.

Simultaneously, at a significance level of 0.01, the Kendall correlation coefficients for city rankings between the Betweenness-based method and both the production-based or consumption-based methods in 2012, 2015, and 2017 were -0.383, 0.612, and 0.433, and -0.183, 0.451, and 0.428, respectively. These results indicate a lower correlation between industry rankings Betweenness method and those either production or consumption methods. Consequently, the Betweenness-based method may offer a fresh perspective that traditional production or consumption-based carbon reduction approaches might not capture.

The carbon emission rankings across different regions in 2012, 2015, and 2017 for the Betweenness-based and production-based methods, as well as for the Betweenness-based and consumption-based methods, are presented in Figure 3, respectively. The solid black dots on the black line represent sectors where the ranking remains the same across both methods. There are only a few points along the black line, indicating that the Betweenness-based method yields different results from both the Production-based and Consumption-based methods. The red dashed box outlines the top 30 sectors ranked by the Betweenness-based method, while the purple dashed box outlines the top 30 sectors ranked by either the Production-based method or the Consumption-based method.

Table 2: Correlation coefficients for the rankings of sectors between the betweenness-based method and the production-based and consumption-based methods.

			Production-based method	Consumption-based method
Betweenness-based method	2012	Correlation	-.383**	-.183 **
		P-Value	6.55×10^{-21}	8×10^{-6}
	2015	Correlation	.612**	.451**
		P-Value	8.37×10^{-51}	2.35×10^{-28}
	2017	Correlation	.433**	.428**
		P-Value	2.54×10^{-26}	1.05×10^{-25}

At the 0.01 level (two-tailed), the correlation is significant.

In Figure 3, there are respectively 23 green dots and 17 blue dots distributed within the red box areas without intersecting the purple box. Among them, 11 green dots and blue dots overlap. This indicates that these sectors are considered critical by the betweenness-based method, while the production-based method and consumption-based method are ignored. For instance, the Production and distribution of tap water sector in Inner Mongolia ranks 3rd according to the betweenness-based method but ranks 221st and 78th according to the production-based method and consumption-based method, respectively. From a comprehensive analysis of Figure 3 (2012, 2015, 2017), it can be observed that the Mining and washing of coal sector in Inner Mongolia, as well as the Manufacture of chemical products sector in Henan, have ranked among the top 30 in implied emissions for several years by betweenness-based method, but they did not rank among the top 30 by traditional methods.

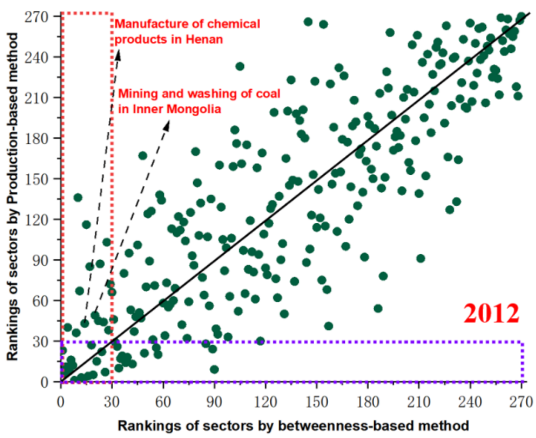

Figure 3a (2012)

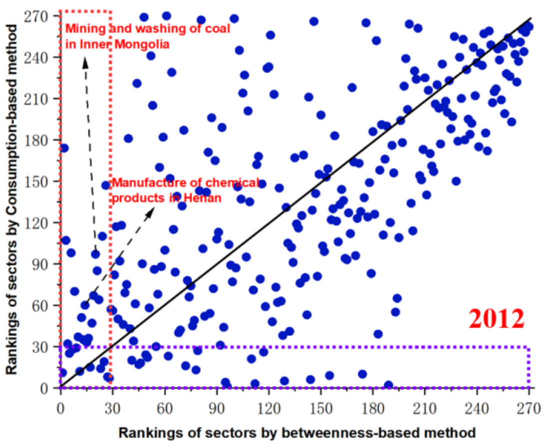

Figure 3b (2012)

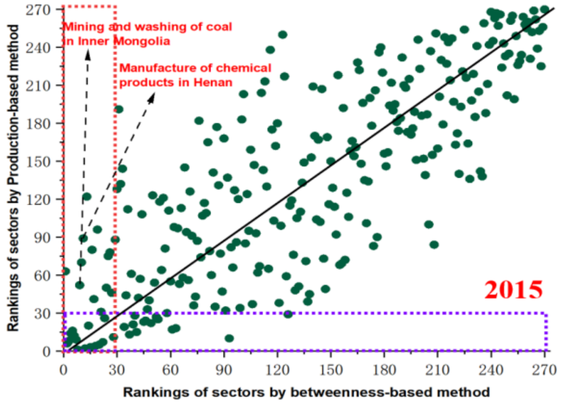

Figure 3c (2015)

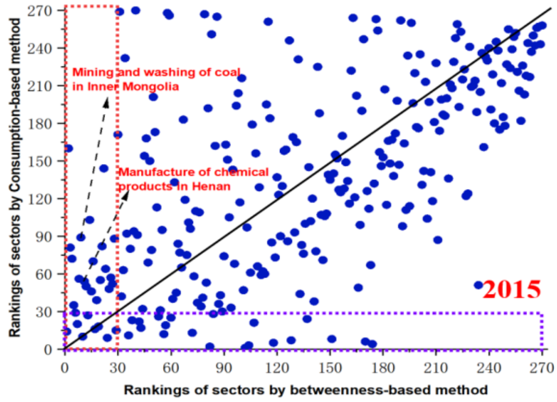

Figure 3d (2015)

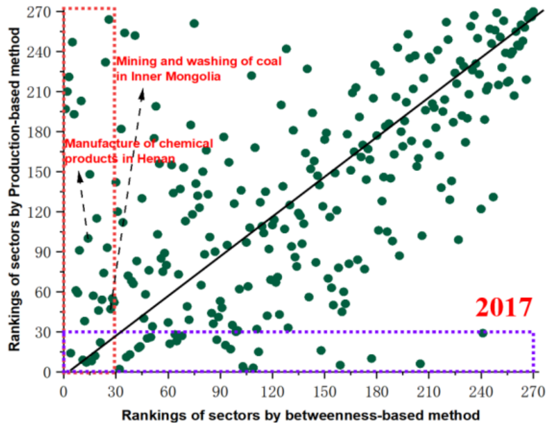

Figure 3e (2015)

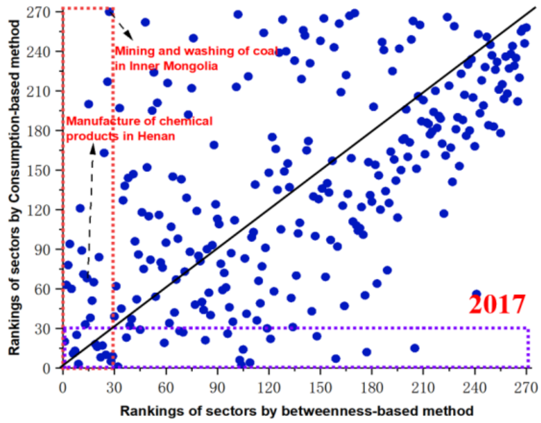

Figure 3f (2015)

Figure 3: The Ranking Comparison of CO2 Emissions between Production-Based and Betweenness-Based Methods, and between Consumption-Based and Betweenness-Based Methods in 2012, 2015, and 2017

3.3 Spatial-temporal Characteristics of Transmission Sectors

Based on the betweenness-based method, carbon emissions in the Yellow River Basin decreased from 2012 to 2017, with a total change of -1117.39 million tons. To gain a clearer understanding of this change, we categorize it into industries with carbon emission increases and decreases. Moreover, the sectors ranking in the top thirty for carbon emission changes showed particularly significant variations, accounting for 79.45% and 70.65% of the total changes in their respective categories. Therefore, this paper will focus on analyzing these provincial-level sectors from two perspectives: carbon emission changes and carbon change ranking (detailed in Figure 4 and Figure 5).

Among the top thirty sectors with changes in carbon emissions, there are eleven sectors with increased carbon emissions, accounting for 36.67% of the total. These mainly include services such as production and distribution of tap water (S26), wholesale and retail trades (S28), and other manufacturing products (S22). As observed from Figure 4, notably within the nine provinces of the Yellow River Basin, the production and distribution of tap water sector ranks among the top thirty in seven provinces. This highlights the significant role played by the production and distribution of tap water industry in carbon emissions. Furthermore, there are notable regional differences within the same sector in terms of carbon emissions. For example, as depicted in Figure 4, in the case of the production and distribution of tap water sector, carbon emissions in Sichuan (P5S26) reach as high as 385.29 million tons, whereas in Qinghai (P8S26), it is only 67.94 million tons.

Among the top thirty sectors in terms of changes in carbon emissions, there are nineteen sectors dedicated to carbon reduction, accounting for 63.33% of the total. These primarily include energy sectors such as smelting and processing of metals (S14), manufacture of chemical products (S12), and production and distribution of electric power and heat power (S24). It is noteworthy that the manufacture of chemical products industry in Shandong (P3S12) ranks first among these industries, making a significant contribution to carbon reduction with a reduction of 547.63 Mt. In the other leading carbon reduction sectors, the smelting and processing of metals industries in Shandong (P3S26), Inner Mongolia (P2S26), Shanxi (P1S26), and Henan (P4S26) contributed 302.56 Mt, 215.27 Mt, 160.75 Mt, and 144.73 Mt respectively.

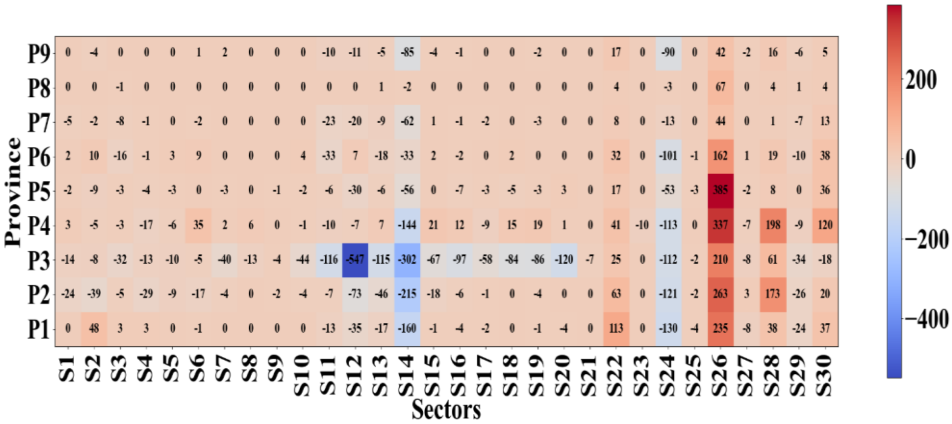

Figure 4: The carbon emission changes of 270 provincial-level sectors in the Yellow River Basin from 2012 to 2017 by the betweenness-based method.

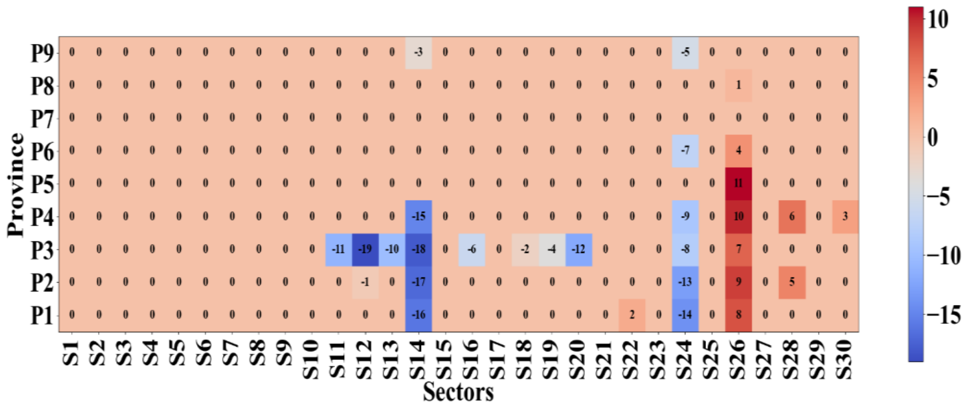

Figure 5: The top 30 sectors of absolute carbon emission changes at the provincial level in the Yellow River Basin based on the betweenness method from 2012 to 2017.

The changes in carbon emissions are influenced by various socio-economic factors, including production technology, population size, and economic structure. Analysis from Figure 6 indicates that the contributions of carbon emission and reduction sectors to carbon emissions vary under different social and economic driving factors. Therefore, this paper conducted a factor analysis on the top thirty sectors of carbon emission changes.

Among the top thirty sectors in terms of emission changes, the production and distribution of tap water stand out as the industry with the highest carbon emission increase, accounting for 63.64% of the total emission increase across industries. The results indicate that the contribution of factors to the production and distribution of tap water industry in provinces such as Sichuan (R2), Henan (R3), Inner Mongolia (R5), Shanxi (R6), Shandong (R8), Shaanxi (R11), and Qinghai (R30) is roughly similar. Among these, input-output technology (ΔL) and per capita final demand (ΔFL) are the primary reasons driving the increase in CO_2 emissions in these provincial sectors. Especially in Sichuan (R2), the production and distribution of tap water resulted in a carbon emission increase of 331.99 million tons due to input-output technology (ΔL) factors, which is equivalent to 428 times the carbon emissions caused by changes in final demand structure (ΔFS). Furthermore, despite the negative impact of the production and distribution of tap water in Shanxi (R6), Henan (R3), Shandong (R8), and Qinghai (R30) on carbon emissions within the final demand structure (ΔFS), they did not trigger significant fluctuations. Overall, except for the final demand structure in some individual provinces, carbon emission intensity (ΔE), input-output technology (ΔL), and per capita final demand (ΔFL) all exert inhibitory effects on carbon reduction in the production and distribution of tap water industry across provinces. Hence, this industry demonstrates a significant carbon-intensive effect.

From the right side of Figure 6, it can be observed that the carbon reduction sectors ranking high in terms of carbon emission changes are influenced by the five factors in a similar trend. The results indicate that the carbon emission intensity (ΔE) and the final per capita demand (ΔFL) of these sectors exhibit a significant positive fluctuation in their impact on carbon emission changes. For example, in the smelting and processing of metals industry in Shandong (R4), Inner Mongolia (R7), Shanxi (R12), and Henan (R13), the contribution values of carbon emission intensity (ΔE) are 877.42 Mt (R4), 784.31 Mt (R7), 435.84 Mt (R12), and 668.06 Mt (R13) respectively. Furthermore, the input-output technology has consistently exhibited a negative effect, with its value far exceeding the sum of positive factors. Taking the top five departments in terms of carbon reduction contribution as examples, they respectively generated 2411.13 Mt (R1), -1382.09 Mt (R4), -930.79 Mt (R7), -700.93 Mt (R12), and -1036.56 Mt (R13) of carbon emissions. Meanwhile, although the population size (ΔP) has a relatively minor influence, it also encourages the leading energy sectors to reduce carbon emissions. Overall, input-output technology emerges as the most crucial factor restraining the increase in CO_2 emissions from carbon reduction industries. This indicates the growing significance of its role in optimizing input-output technology.

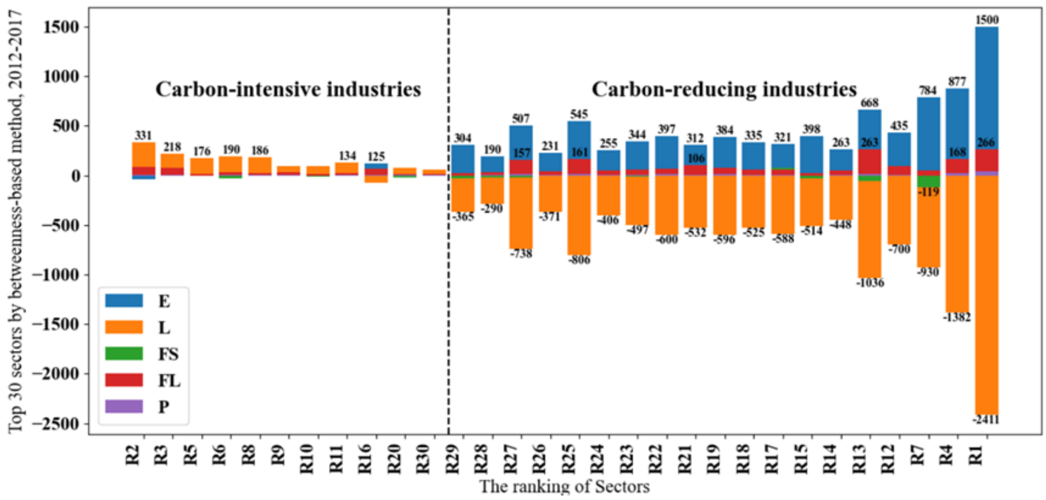

Figure 6: The structural decomposition analysis of carbon emissions from influencing factors by the betweenness-based method from 2012 to 2017.

(E: Carbon emission intensity, L: Input-output technology, FS: Final demand structure, FL: Per capita final demand, P: Population size).On the left side of the dashed line are the sectors contributing to carbon emission increase, with carbon emission changes ranking in increasing order from the dashed line to the far left. On the right side of the dashed line are the sectors contributing to carbon emission reduction, with carbon emission changes ranking in increasing order from the dashed line to the far right. Specific change rankings are indicated on the x-axis.

4. Discussion

Firstly, besides continuing to monitor carbon emission sectors that have remained stable and crucial over the years, we should pay more attention to sectors showing significant upward trends in rankings according to betweenness-based methods. Enhancing the production efficiency of these sectors can facilitate carbon emissions reduction. The results indicate that from 2012 to 2017, heavy industries such as the Manufacture of chemical products, Smelting and processing of metals, and Manufacture of non-metallic mineral products played a stable and crucial role in carbon emissions contribution. However, in 2012, 2015, and 2017, the production and distribution of tap water sector in Sichuan (ranked 180, 197, 1), Henan (ranked 135, 124, 2), and Inner Mongolia (ranked 158, 165, 3), indicating its increasing importance as a transmission node in the multi-regional implicit carbon network within the Yellow River Basin. Meanwhile, the growth trends in industries such as Wholesale and retail trades and other services, are consistent with the production and distribution of the tap water industry. These sectors are not traditional heavy industries or high-emission industries, yet their contributions to CO_2 emissions cannot be overlooked. Hence, future carbon reduction efforts should not only focus on traditional heavy industries but also pay attention to emerging sectors such as public services and light industries. It is essential to comprehensively consider the contributions from various sectors to formulate targeted emission reduction policies and measures.

Moreover, the betweenness-based method can help identify crucial sectors overlooked by either consumption-based or production-based methods. The results indicate that in 2017, 11 provincial-level industries entered the top 30 rankings based on the betweenness-based method but were neglected by both consumption-based and production-based methods. These 11 provincial sectors include the Production and distribution of tap water industry in Shanxi (P3S12), Inner Mongolia (P10S12), Henan (P19S12), Shaanxi (P12S12), and Qinghai (P16S12), as well as the Manufacture of chemical products industry in Shandong and Henan, and the Coal mining and dressing products and other manufacturing products in Shanxi and Inner Mongolia. It is noteworthy that the Mining and washing of coal sector in Inner Mongolia and the Manufacture of chemical products sector in Henan have consistently ranked in the top 30 based on the betweenness-based method for the years 2012, 2015, and 2017, while they have consistently failed to enter the top 30 based on traditional methods. This further highlights the advantages of the betweenness-based method in identifying crucial emitting industries and addressing carbon emissions issues from a singular perspective.

Thirdly, we should pay more attention to the provincial-level transportation sectors that experienced significant changes between 2012 and 2017. From a betweenness perspective, the top 30 provinces with significant changes can be mainly categorized into two types: carbon emissions increase and carbon emissions reduction. Therefore, it is necessary to actively analyze the carbon reduction factors in the metal smelting and rolling processing industry of provinces such as Shandong (R1), Shandong (R4), Inner Mongolia (R7), Shanxi (R12), and Henan (R13), to guide the formulation of more targeted emission reduction policies for sectors contributing significantly to carbon emissions, such as the water production and supply industry in provinces like Sichuan (R2), Henan (R3), Inner Mongolia (R5), Shanxi (R6), and Shandong (R8). Enhancing the intermediate input efficiency of such carbon-emitting sectors may contribute to mitigating CO_2 emissions.

Lastly, further attention is needed on the influencing factors of carbon emissions from crucial provincial-level sectors to supplement existing policies and guide CO_2 reduction at the provincial level. The results indicate that for the reduction of carbon emissions in sectors such as the manufacture of chemical products (R1) in Shandong, and the smelting and processing of metals in provinces like Shandong (R4), Inner Mongolia (R7), Shanxi (R12), and Henan (R13), their input-output technologies make the greatest contribution to the decrease in CO_2 emissions, while carbon emission intensity and per capita final demand are crucial driving factors for increased CO_2 emissions. Specific policies are as follows:

1) The government can formulate policies to encourage industries to develop towards low pollution and low energy consumption and to implement rewards and penalties to promote the improvement of energy efficiency.

2) Optimizing the intermediate input structure is crucial, such as upgrading existing smelting furnaces and rolling equipment to enhance energy efficiency during the production process.

3) The per capita final demand contribution rate is gradually increasing, and it is necessary to establish a market-oriented low-carbon product system to reduce the production and consumption of high-carbon products.

Meanwhile, for provinces such as Sichuan (R2), Henan (R3), Inner Mongolia (R5), Shanxi (R6), and Shandong (R8), where industries such as Production and distribution of tap water contribute to carbon emission increases, their input-output technology and carbon intensity have been identified as the main factors promoting carbon emission growth from 2012 to 2017. Specific policies are outlined as follows:

1) In optimizing input-output structure, emphasis can be placed on the upgrading and maintenance of urban pipelines and wastewater treatment facilities in provinces such as Sichuan, Henan, Inner Mongolia, and Shanxi, to indirectly reduce carbon emissions.

2) To reduce carbon emission intensity, the key lies in improving energy utilization efficiency. For instance, utilizing clean energy sources such as solar or wind power to operate water pumps or wastewater treatment plants can replace traditional fuel or electricity-driven methods.

5. Conclusions

In this study, we used a betweenness-based framework to identify critical provincial-level departments in the nine provinces of the Yellow River Basin for the years 2012, 2015, and 2017. Subsequently, we elucidated the correlation betweenness-based with production-based or consumption-based methods and focused on the top thirty sectors ranked by changes in carbon emissions. The main findings are as follows.

Both production-based and consumption-based methods overlook certain critical provincial transportation sectors, such as the Mining and washing of coal sector in Inner Mongolia and the Manufacture of chemical products sector in Henan. Improving the efficiency of these sectors might lead to a reduction in carbon emissions upstream in the supply chain. From an industry perspective, the focus of carbon emissions is gradually shifting from heavy industries such as the manufacture of chemical products and metal smelting and rolling processes to light industries such as the production and distribution of tap water. From the perspective of provincial departments, the chemical products manufacturing industry in Shandong, as well as the metal smelting and rolling processing industry in Shandong, Inner Mongolia, Shanxi, and Henan provinces, are considered key sectors for carbon reduction. Meanwhile, the water production and supply industries in Sichuan, Henan, Inner Mongolia, Shanxi, and Shandong provinces are regarded as critical sectors for carbon increase. Furthermore, input-output technology makes significant contributions to sectors reducing carbon emissions. However, these contributions are largely offset by carbon intensity and per capita final demand. Simultaneously, input-output technology is also a primary driver of CO_2 emissions in sectors experiencing emission increases. Optimizing input-output technology can indirectly promote CO_2 reduction. Building upon this foundation, we propose several policy recommendations, such as closely monitoring the production efficiency of key sectors, optimizing the structure of intermediate input, and enhancing energy utilization efficiency, thereby reducing carbon dioxide emissions.

References

[1] Liu Z, Deng Z, Davis S, et al. Monitoring global carbon emissions in 2022. Nature Reviews Earth & Environment, 2023, 4(4): 205-206.

[2] Liu Z, Deng Z, Davis S J, et al. Monitoring global carbon emissions in 2021. Nature Reviews Earth & Environment, 2022, 3(4): 217-219.

[3] Chen X, Lin B. Towards carbon neutrality by implementing carbon emissions trading scheme: Policy evaluation in China. Energy Policy, 2021, 157:112-115.

[4] Liu J, Zhang Y, Pu L, et al. Research on the impact of energy efficiency on green development: A case study of the Yellow River Basin in China. Energies, 2023, 16(9): 36-60.

[5] Gong W, Zhang H, Wang C, et al. Analysis of urban carbon emission efficiency and influencing factors in the Yellow River Basin. Environmental Science and Pollution Research, 2023, 30(6): 14-55.

[6] Dong H, Dai H, Geng Y, et al. Exploring impact of carbon tax on China's CO2 reductions and provincial disparities. Renewable and Sustainable Energy Reviews, 2017, 77:596-603.

[7] Liang S, Qu S, Xu M. Betweenness-based method to identify critical transmission sectors for supply chain environmental pressure mitigation. Environmental Science & Technology, 2016, 50(3): 1330-1337.

[8] Wang J, Du T, Wang H, et al. Identifying critical sectors and supply chain paths for the consumption of domestic resource extraction in China. Journal of cleaner production, 2019, 208:77-86.

[9] Hu M, Chen S, Wang Y, et al. Identifying the key sectors for regional energy, water and carbon footprints from production-, consumption-and network-based perspectives. Science of the Total Environment, 2021, 764:142-145.

[10] Liu X, Peng R, Bai C, et al. Exploring key sectors of CO2 emissions and driving factors to spatiotemporal evolution in China from multiple perspectives. Environmental Science and Pollution Research, 2023, 30(7): 685-700.

[11] Yuan X, Sheng X, Chen L, et al. Carbon footprint and embodied carbon transfer at the provincial level of the Yellow River Basin. Science of the total environment, 2022, 803:149-156.

[12] Wang Y, Zhao H, Li L, et al. Carbon dioxide emission drivers for a typical metropolis using input–output structural decomposition analysis. Energy Policy, 2013, 58(3): 12-18.

[13] Leontief W W. Quantitative input and output relations in the economic systems of the United States. The review of economic statistics, 1936, 105-125.

[14] Feng C, Tang X, Jin Y, et al. Regional energy-water nexus based on structural path betweenness: A case study of Shanxi Province, China. Energy Policy, 2019, 127: 102-112.

[15] Wang P, Li Y, Huang G, et al. A multi-scenario factorial analysis and multi-regional input-output model for analyzing CO2 emission reduction path in Jing-Jin-Ji region. Journal of Cleaner Production, 2021, 300(12): 67-82.

[16] Freeman L C. A set of measures of centrality based on betweenness. Sociometry, 1977, 35-41.

[17] Zheng H, Zhang Z, Wei W, et al. Regional determinants of China's consumption-based emissions in the economic transition. Environmental Research Letters, 2020, 15(7): 74-101.

[18] Shan Y, Guan D, Zheng H, et al. China CO2 emission accounts 1997–2015. Scientific data, 2018, 5(1): 1-14.

[19] Shan Y, Huang Q, Guan D, et al. China CO2 emission accounts 2016–2017. Scientific data, 2020, 7(1): 54.