

Identification of key carbon emitters from the perspective of network analysis

Lijuan Xia, Yongli Li^{*}, Xiaochen Ma

School of Economics and Management, Harbin Institute of Technology, Harbin 150001, China

ARTICLE INFO

Keywords:

Carbon emissions
Network analysis
Embodied CO₂ flows
Environmental input–output analysis

ABSTRACT

Climate risks are sharpened and adaptation actions are urgent. However, the economic system is a whole composed of numerous interrelated and interactive economic elements and poses a challenge for carbon mitigation. To explore the carbon emission effects of producers in complex economic systems and formulate targeted carbon mitigation policies, this study constructs three indicators to assess the carbon emission effect embodied in the economy through network analysis. More specifically, the total emission effect of each producer is measured by the push-type effect and pull-type effect and tested by comparing with the hypothetical extraction method. Taking China as an example, the results show that the effect of different sectors on carbon emissions varies greatly. The production and distribution of electric power and heat power is a key sector dominated by the push-type effect. This is, its carbon emissions are mainly triggered by the demands of its downstream sectors. The total emission effects of Construction and Smelting and processing of metals are also strong, but their pull-type effect is dominant. According to the dominant effect in the total emission effect, we can draft targeted emission reduction strategies.

1. Introduction

Due to excessive greenhouse gas emissions, extreme weather events occur frequently, such as drought and high temperature, etc., which leads to climate risks and threatens ecosystem stability. Note that the greenhouse effect represented by carbon dioxide is the major inducer of climate change. Nowadays, many regions and countries around the world have issued a series of policies and measures to curb climate risk and stabilize ecosystems. Meanwhile, carbon emission has become a hot topic in academia, and some scholars have discussed the pattern of carbon emission flows and evolution (Hickman et al. 2010; Xi et al. 2019). However, the economic system is a whole composed of numerous interrelated and interactive economic elements. Carbon emissions embodied in economic systems pose challenges to assessing the emission effects of producers and formulating personalized carbon mitigation policies. In this context, this study aims to answer the questions: (a) how to assess the carbon emission effects of producers in complex economic systems? and (b) what aspects deserve more consideration when formulating carbon mitigation policies?

Some studies focus on carbon emissions and attempt to identify the key industries. For instance, the method based on energy consumption

(Xia et al., 2020; Sanches-Pereira et al., 2016) estimates CO₂ emissions and identifies the key sectors. The energy-related method only reflects carbon emissions, without considering the carbon transfer embodied in the economy. With the in-depth development of the economy, the flow and spatial distribution of productive factors have become more extensive which is usually accompanied by massive carbon emissions (Li et al., 2020). The extensive carbon emission flows among economies driven by economic transactions have evolved into a complex interwoven network, and become an inalienable part of carbon emissions. Hence, our first motivation is to construct indicators to assess the carbon emission effects, which not only considers the carbon emissions produced by producers themselves but also counts the carbon flows embodied in the economic production chain.

To depict the inter-sectoral carbon emissions embodied in the economic production chain, prior studies constructed the carbon flow network (Zhang et al., 2017). Based on carbon flow networks, Jia et al. (2020) and Ma et al. (2019) respectively estimate the emissions of each sector based on the network cascade and node degree and then identify the key emission sectors. Though these studies identify the key emitters, these methods have certain limitations in revealing the internal mechanisms that trigger the carbon emissions of sectors. To fill the gap,

^{*} Corresponding author.

E-mail address: liyongli@hit.edu.cn (Y. Li).

<https://doi.org/10.1016/j.ecolind.2023.110284>

Received 29 August 2022; Received in revised form 25 March 2023; Accepted 18 April 2023

Available online 23 April 2023

1470-160X/© 2023 The Author(s). Published by Elsevier Ltd. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

considering the direction of carbon flows, this study splits the carbon emission into two types and constructs two sub-indicators: pull-type effect and push-type effect, which correspond to the carbon inflows and carbon outflows respectively. Accordingly, we can further locate the key factor that triggers carbon emissions and guide the formulation of more pertinent carbon mitigation policies. This is, according to the proportion of the push effect and pull effect, more attention should be paid to the party that causes carbon emissions, which is the second motivation.

Once the assessment method of carbon emission effects is constructed based on social network theory, which not only solves the identification of key carbon emitters but also has a wider range of applications in practice. Scholars have proposed some methods to quantify and estimate carbon emissions. A common method is the hypothetical extraction method, which depends on the input–output table and estimates carbon emissions by replacing these elements of row and column from the technical coefficient matrix (Ali, 2015; Wang et al. 2021). This method needs the input–output data as the basis, which limits its application scope. Therefore, this study is committed to proposing an assessment method based on the local production chains of producers. On the one hand, this method can estimate the emission effect only based on the carbon flows among its neighbors, without relying on the global data of the system. On the other hand, fewer data requirements make this method can break through the input–output field and have a wider application, such as estimating the carbon emissions of any enterprise in the supply chain, etc.

The purpose of this study is to construct a new method to assess the carbon emission effects through network analysis and reveal the carbon emission mechanism. Compared with the existing research, the contributions of this study are as follows. First, different from the methods of energy consumption (Xia et al., 2020), this study considers the carbon flows embodied in the economy and constructs a novel assessment method of carbon emission effects from the perspective of network analysis, including direct and indirect emissions. Second, prior studies identify key emitters according to the network node characteristics and cascade effect (Ma et al., 2019; Jia et al. 2020). Compared with the existing identification methods of key carbon emitters from the perspective of the network, the method proposed in this study further considers the carbon emissions of upstream and downstream neighbors and tracks the source of carbon emissions, which not only reveals the internal interaction mechanism between carbon emitters but also provides a reference for formulating more targeted carbon mitigation policies. Third, the method constructed in this study is mainly estimated by the interaction between the producer and its neighbors, without traversing the global network. This method overcomes the data limitations and prolongs the application scope.

The remaining parts of this study are organized as follows. Section 2 depicts data sources, and constructs the estimation method of carbon emission effects. Section 3 applies this method and analyzes the results. Section 4 tests our method and draw some management implications. Finally, section 5 summarizes the conclusion of this study.

2. Data and methodology

This section first introduces the data source. Then, based on the social network theory, we constructed three indicators to assess the carbon emission effect (i.e., pull-type effect, push-type effect, and total emission effect).

2.1. Data

In this study, we use the multi-region input–output table in 2017 published by China Emission Account and Datasets (CEADS) ^[1] for

^[1] China Emission Account and Datasets (CEADS): <https://www.ceads.net.cn/>.

result analysis. The data includes 31 regions, excluding Macau, Hong Kong, and Taiwan. Each region contains 42 sectors. Then the assessment method of this study is applied to identify the key carbon sectors in China and provide some implications for the formulation of carbon mitigation policies. Based on the input–output data of China, we conduct an empirical analysis of the method proposed in this study.

2.2. Methodology

2.2.1. Construction of carbon flow network

Carbon flows are calculated by the environmental multi-regional input–output (MRIO) model, which is derived from the structure of the traditional MRIO model and characterize the carbon footprint embodied in economic transactions. The environmental MRIO model has been widely used in previous studies, such as air pollutants (Zhang et al., 2017), and land use (Hong et al., 2022). Specifically, the calculation process is as follows.

In input–output analysis, the input–output table depicts the interdependencies among sectors within a certain period, and the technical coefficient matrix A portrays proportional relationships that the goods or services produced by one sector are consumed by the unit total output of another sector during the production and operation process. Hence, according to the final demand matrix F formed by the final demand of each sector in the input–output table, the total output X of the whole economic system can be deduced, as shown in Eq. (1).

$$X = AX + F = (I - A)^{-1}F = (I + A + A^2 + \dots + A^n + \dots)F \quad (1)$$

here, $L = (I - A)^{-1}$ is the Leontief inverse matrix, where element l_{j-i} is the Leontief inverse coefficient indicating that the unit final demand of producer i requires the input amount of the producer j . $(I + A + A^2 + \dots + A^n + \dots)$ is the Taylor expansion of the Leontief inverse matrix, which portrays direct and indirect emissions of the economic production process. The direct carbon emission intensity φ_i ($\varphi_i = c_i/x_i$) of producer i is estimated as the ratio of direct carbon emission c_i to the total output x_i . Combined with Eq. (1), the consumption-based carbon emission C can be calculated by extending the MRIO model with carbon emission intensity $\hat{\varphi}$, as shown in Eq. (2).

$$C = \hat{\varphi}X = \hat{\varphi}(I + A + A^2 + \dots + A^n + \dots)F = \begin{bmatrix} \varphi_1 l_{1-1} f_1 & \varphi_1 l_{1-2} f_2 & \dots & \varphi_1 l_{1-n} f_n \\ \varphi_2 l_{2-1} f_1 & \varphi_2 l_{2-2} f_2 & \dots & \varphi_2 l_{2-n} f_n \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_n l_{n-1} f_1 & \varphi_n l_{n-2} f_2 & \dots & \varphi_n l_{n-n} f_n \end{bmatrix} F \quad (2)$$

The matrix C is carbon flows embodied in the production process, where the element c_{j-i} represents the carbon emissions of producer j triggered by the final demand of producer i . $\hat{\varphi}$ is the diagonal matrix composed of φ_i . Taking producers as nodes and carbon flows as edges, a directed weighted network $G(V, E)$ that portrays the carbon flows embodied in the economy is constructed. V and E are nodes and edges set of the network G , respectively.

Since the sectors in different regions are the same, a multilayer network can be constructed, and the schematic diagram is shown in Fig. 1, each layer represents a region and the nodes in the layer represent the production sectors of each region. The edges among nodes capture the carbon flows, where the weight of edges represents the volumes of carbon flows. The carbon flow in the network is directional, including carbon outflows and carbon inflows, which correspond to the supply-push effect and demand-pull effect respectively. For node i , B_i is the neighbor of node i . Furthermore, there are directional self loops in the network (Jiang et al., 2021), the self-loops are also included, which ensures the consistency and accuracy of the carbon emission effect measured.

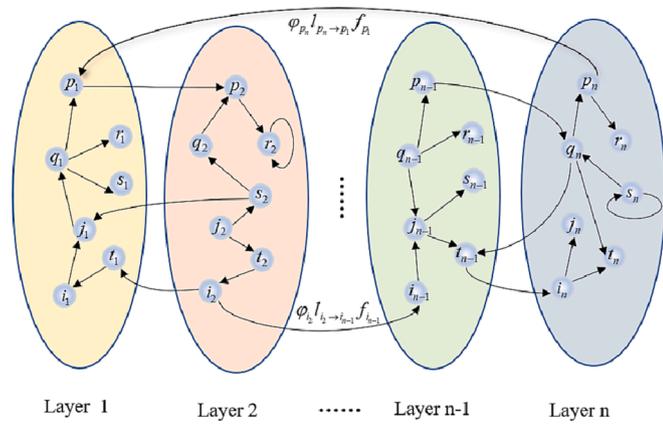


Fig. 1. Schematic diagram of multilayer network.

2.2.2. Indicators Construction of carbon emission effect

Due to carbon emissions embodied in the economic production chain, the carbon emission effects of producers on the economic system depend not only on their emissions but also upon their linkages with local neighbors, which hinges on the weight and direction of the interactions. It is noteworthy that $\hat{\varphi}(A^2 + \dots + A^n + \dots)F$ donates the carbon emissions embodied in the intermediate inputs of all producers, and the embodied carbon emissions gradually decrease with the growth of links (Jiang et al., 2021). Inspired by the Taylor expansion of total emissions, we concentrate on the interaction between nodes and their neighbors to assess their effects on carbon emissions. In addition, the demand pull and supply push of producers are the two directions that cause carbon emissions. According to the direction of nodes in weighted-directed networks, we classify the carbon flows as the upstream demand-driven type and the downstream supply push type based on the link interactions of a sector with its direct neighbors and then define the assessment indicators of pull-type effect (PLE), push-type effect (PSE), respectively. The environmental pollution caused by the push effect and the pull effect is indiscriminate, so the total emission effect (TEE) can be measured by the sum of the pull-type effect and push-type effect (PSE).

(1) Pull-type effect (PLE).

Pull-type effect (PLE) is the carbon emission effect generated along with the economic transaction process of product input from upstream neighbors to local production, which corresponds to the inflows in the carbon flow network. The supports from upstream neighbors display the final demands of emitter i pull the carbon flows of its upstream neighbor j . For neighbor j , the ratio of outflows to producer i to its total outflows ($\varphi_j l_{j \rightarrow i} / \sum_{v \in \{B_j, j\}} \varphi_j l_{j \rightarrow v} f_v$) reflects the pull strength of producer i . The higher the value, the stronger the pull-type effect of producer i on the upstream neighbor j , indicating that more carbon emissions of neighbor j are triggered by producer i . Meanwhile, the carbon inflows of neighbor j can also cascade to producer i , further enhancing the pull-type effect of producer i on the global network. In other words, the carbon inflows of neighbor j ($\sum_{u \in \{B_j, j\}} \varphi_u l_{u \rightarrow j} f_j$) as a proxy indirectly enhance the pull-type effect of producer i . Considering both direct and indirect effects, we define the pull-type effect (PLE) of producer i with its neighbor B_i , as Eq. (3).

$$PLE_i = \sum_{j \in \{B_i, i\}} \left(\frac{\varphi_j l_{j \rightarrow i}}{\sum_{v \in \{B_j, j\}} \varphi_j l_{j \rightarrow v} f_v} \sum_{u \in \{B_j, j\}} \varphi_u l_{u \rightarrow j} f_j \right) \quad (3)$$

(2) Push-type effect (PSE).

The Push-type effect (PSE) is the carbon emission effect accompanied by producer i providing products for its downstream neighbors' production and final consumption, which corresponds to the outflows in the carbon flow network. Corresponding to the pull-type effect, the push-type effect of producer i depicts its reaction strength to its

downstream neighbors. The ratio of inflows from producer i to all inflows of producer k ($\varphi_i l_{i \rightarrow k} f_k / \sum_{u \in \{B_k, k\}} \varphi_u l_{u \rightarrow k} f_k$) mirrors the support strength of producer i to downstream neighbor k . Also, the influence of producer i further propagates in the network through its neighbor k , and the influence is captured by the outflows of downstream neighbor k ($\sum_{v \in \{B_k, k\}} \varphi_k l_{k \rightarrow v} f_v$). Similarly, to ensure the accuracy of the push effect measured from the supply perspective, its self-connection cannot be ignored, and the self-loop flows from the perspective of supply are also included. Formally, the push-type effect of emitter i is defined as Eq. (4).

$$PSE_i = \sum_{j \in \{B_i, i\}} \left(\frac{\varphi_i l_{i \rightarrow j} f_j}{\sum_{u \in \{B_k, k\}} \varphi_u l_{u \rightarrow k} f_k} \sum_{v \in \{B_k, k\}} \varphi_k l_{k \rightarrow v} f_v \right) \quad (4)$$

(3) Total Emission Effect (TEE).

The majority of producers in the input-output process of the economic system have both carbon outflows and carbon inflows (see Fig. 1). In the carbon flows network, each carbon flow corresponds to an inflow and outflow, which is an outflow for the source node and inflow for the node targeted by the arrow, and its relative importance to the source node and target node is also different. The push effect and pull effect defined in this study capture these two effects of carbon flows respectively. In this context, the total emission effects of producers are determined by their interaction with upstream and downstream neighbors which correspond to their consumption and production respectively. This is, the total emissions depend not only on the inflow carbon footprint but also on the outflow carbon footprint. Hence, the total emission effect (TEE) is assessed through the summation of the pull-type effect and push-type effect to systematically and comprehensively evaluate the influence of producers. As shown in Eq. (5),

$$TEE_i = PLE_i + PSE_i \quad (5)$$

Note that the proportion of the pull-type effect and the push-type effect in the total emission effect reveals the source of carbon emissions, that is, which effect plays an important role in the total emission effect, and locates the direction for formulating emission mitigation policies. In addition, according to the definition of push-type effect and pull-type effect, we find that the final demand of node i is the public factor that affects its pull-type effect, while the carbon emission intensity is the public factor that affects its push-type effect. This property further locates the key factors of emission reduction.

3. Results

This section takes China as an example and applies the above indicators to unfold an empirical analysis. To facilitate the display of results, we merge the same sectors of the multilayer network and form a network containing 42 sectors. Afterward, the total emission effect of each sector, as well as the ratio of push-type effect and pull-type effect, are calculated. The total emission effect of each sector is normalized by min-max scaling, where the total emission effect result range between 0 and 1, to provide a more intuitive demonstration, as shown in Table 1.

Table 1 reveals that some sectors have a profound influence on the carbon emissions of the economic system, and the sub-effects that dominate their total emission effects vary greatly. Comparing the proportion of the pull-type effect (PLE) and push-type effect (PSE) in the total emission effect points out the direction that dominates the total emission effects of sectors, which suggests that priority should be given to emission reduction on the corresponding leading effect. Specifically, the total emission effect of Production and distribution of electric power and heat power is not only far greater than other sectors but also its push-type effect is dominant. Similarly, there are Smelting and processing of metals, Mining and washing of coal, Transport, storage, and postal services, and Manuf. of non-metallic mineral products, etc. whose total impact ranks at the top and push-type effect accounts for more than 97 % of the total emission effect. The results indicate that the carbon emissions of these sectors are mainly triggered by the demands of their

Table 1
Carbon emission effects of 42 sectors.

Code	Sectors	Rank	TEE	PSE	PLE
01	Agriculture, Forestry, Animal Husbandry and Fishery	20	0.0014	57.3%	42.7%
02	Mining and washing of coal	4	0.0192	99.9%	0.1%
03	Extraction of petroleum and natural gas	22	0.0009	99.7%	0.3%
04	Mining and processing of metal ores	37	0.0002	99.6%	0.4%
05	Mining and processing of nonmetal and other ores	40	0.0001	97.5%	2.5%
06	Food and tobacco processing	14	0.0019	7.2%	92.8%
07	Textile industry	32	0.0004	8.3%	91.7%
08	Manufacture of leather, fur, feather and related products	18	0.0015	0.5%	99.5%
09	Processing of timber and furniture	33	0.0004	3.1%	96.9%
10	Manufacture of study, printing and articles for culture, education and sport activity	30	0.0005	27.4%	72.6%
11	Processing of petroleum, coking, processing of nuclear fuel	7	0.0042	98.1%	1.9%
12	Manufacture of chemical products	19	0.0014	61.8%	38.2%
13	Manuf. of non-metallic mineral products	6	0.0105	99.3%	0.7%
14	Smelting and processing of metals	3	0.0213	99.5%	0.5%
15	Manufacture of metal products	29	0.0005	19.1%	80.9%
16	Manufacture of general-purpose machinery	15	0.0018	6.9%	93.1%
17	Manufacture of special purpose machinery	12	0.0022	5.3%	94.7%
18	Manufacture of transport equipment	10	0.0022	2.6%	97.4%
19	Manufacture of electrical machinery and equipment	16	0.0017	5.4%	94.6%
20	Manufacture of communication equipment, computers and other electronic equipment	13	0.0019	0.9%	99.1%
21	Manufacture of measuring instruments	39	0.0002	3.6%	96.4%
22	Other manufacturing and waste resources	41	0	69.0%	31.0%
23	Repair of metal products, machinery and equipment	11	0.0022	100.0%	0.0%
24	Production and distribution of electric power and heat power	1	1	100.0%	0.0%
25	Production and distribution of gas	35	0.0003	86.0%	14.0%
26	Production and distribution of tap water	42	0	22.2%	77.8%
27	Construction	2	0.0276	0.1%	99.9%
28	Wholesale and retail trades	8	0.0023	76.9%	23.1%
29	Transport, storage, and postal services	5	0.0141	97.0%	3.0%
30	Accommodation and catering	26	0.0006	8.7%	91.3%
31	Information transfer, software and information technology services	23	0.0009	2.2%	97.8%
32	Finance	28	0.0005	39.4%	60.6%
33	Real estate	21	0.0010	4.4%	95.6%
34	Leasing and commercial services	27	0.0006	76.8%	23.2%
35	Scientific research	25	0.0006	0.1%	99.9%
36	Polytechnic services	38	0.0002	23.3%	76.7%
37	Administration of water, environment, and public facilities	34	0.0004	7.7%	92.3%
38	Resident, repair and other services	31	0.0004	50.6%	49.4%
39	Education	24	0.0008	1.9%	98.1%
40	Health care and social work	9	0.0023	0.2%	99.8%
41	Culture, sports, and entertainment	36	0.0003	5.9%	94.1%
42	Public administration, social insurance, and social organizations	17	0.0015	1.1%	98.9%

Note. TEE represents the total emission effect. The PSE and PLE columns display the proportion of push-type effect and pull-type effect in the total emission effect.

downstream sectors. As the source of carbon emissions, the improvement of their carbon emission intensity deserves more attention when formulating carbon mitigation policies.

As for the key sectors where the pull-type effect is dominant, the total effect of Construction ranks second, and the pull-type effect accounts for 99.9%. In other words, construction has more carbon inflows. Similarly, there are Health care and social work and Manufacture of transport equipment, whose pull-type effect accounts for more than 97% of the total emission effect. This result is consistent with the economic characteristics of China. For such sectors with more carbon inflows, regulating their demand can widely radiate to the upstream sector and achieve effective emission reduction when formulating emission reduction policies. Hence, demand control is a more effective emission reduction strategy for such sectors.

4. Comparison and discussion

4.1. Method test

We make a comparative analysis with the hypothetical extraction method (HEM) to test and verify the methods constructed in this study. The HEM is a classical and widely used method to measure inter-sectoral linkages and the importance of sectors (Ali, 2015). Concretely, we calculate the changes in carbon emission of each sector using the HEM and rank their importance, and then compare it with the total emission effect (TEE) calculated by our method. Meanwhile, we employ Spearman rank correlation to test the consistency of the sector's carbon emission rank under the two methods (Kumar and Abirami, 2018). The larger the correlation coefficient, the more consistent our results are with HEM, and the more reliable our method is. The comparison results are shown in Fig. 2 (HEM is the hypothetical extraction method, and TEE is the total emission effect). As depicted in Fig. 2, the Spearman rank correlation coefficient of inter-provincial sectors under the two methods is 0.856 and significant at the 1% level. The result indicates that the identification method in this study has a high consistency with the results estimated by the hypothetical extraction method, which proves the effectiveness of the method constructed in this study.

4.2. Indicator analysis

To assess the carbon emission effects and reveal the internal mechanism that causes carbon emissions, this study proposes three indicators (i.e., total emission effect, pull-type effect, and push-type effect) based on the network analysis. The influence of nodes in networks depends on themselves and their neighbors. The carbon flows embodied in the production chain portray direct and indirect emissions. Inspired by previous research, we concentrate on the interaction between nodes and their neighbors to assess their effects on the carbon emissions of the

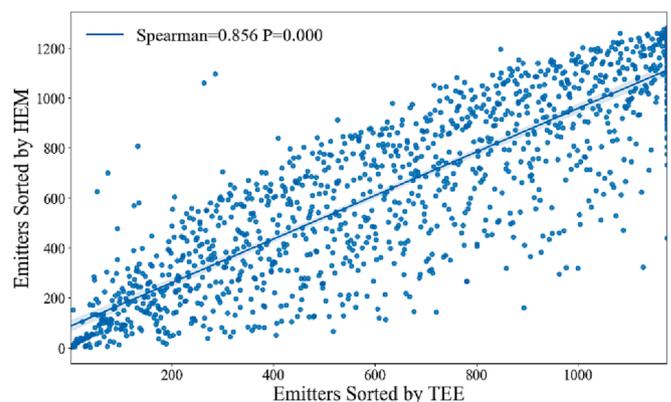


Fig. 2. Comparison and test of methods.

economic system. According to the direction of edges in weighted-directed networks, we assess the pull-type effect and push-type effect. The total emission effect is the sum of the pull-type effect and push-type effect.

The total emission effect assesses the influence of each sector under a framework, and the normalized results are more convenient for comparison. As displayed in Table 1, the total emission effect not only identifies the key emission sectors but also indicates the differences in their effects. The pull-type effect and push-type effect correspond to the inflows influence and outflows influence in the carbon flow network respectively. When given a production structure, the demand of node i drives the production of upstream neighbors and generates pull-type effects, and the carbon emission intensity of node i is the key factor to determine its downstream carbon flows, this is the push-type effect. This property further locates the sources of carbon emissions and suggests that the pull-type effect and push-type effect can be alleviated by adjusting the demand and carbon emission intensity, respectively.

Theoretically, the indicator method constructed in this study enriches the existing carbon emission assessment methods (Jia et al., 2020; Xia et al., 2020; Ma et al., 2019; Ali, 2015). Different from the previous methods that delete sectors and traverse the global, the prominent contribution of our method is that we assess the emission effects from the perspective of the demand-driven type and the downstream supply push type, which can provide a more detailed reference for carbon emission reduction. According to the push effect and pull effect, the government can locate whether the key triggered carbon emissions is upstream or downstream, and pay more attention to the regulation of the dominant effect. Furthermore, the indicators only depend on the local carbon flows, relaxing the dependence on global data, and also have certain application value in the supply chain and other fields.

4.3. Policy implication

In practice, the indicators constructed have significance to policy-makers and managers. Based on the above research results, more pertinent carbon mitigation strategies can be formulated by the following means. First, more attention should be paid to high-emission sectors according to the total emission effects. For example, compared with the production and distribution of tap water, the production and distribution of electric power and heat power, as well as construction, have a greater effect on carbon emissions, that is, they have an important influence on China's carbon emissions. Therefore, more efforts should be centered on emission reduction in such sectors.

Then locate the carbon emission sources of high-emission sectors and give priority to formulating carbon mitigation policies. By more reasonable allocation of limited mitigation resources in emission mitigation, the carbon emissions in the corresponding direction can be mitigated by adjusting the demand or carbon emission intensity. Specifically, for sectors dominated by the push-type effect, such as Production and distribution of electric power and heat power, the improvement of carbon emission intensity is the key to reducing carbon outflows, and thus greatly diminishes its total emission effect. On the contrary, the sector that dominates the pull-type effect should be devoted to demand adjustment, to mitigate the upstream carbon inflows.

This study proposes three indicators to assess the emission estimate effects of producers in complex systems and tests the robustness of the indicators. Taking China as an example, we conduct an empirical analysis and draw some management implications. In fact, the situations embedded in international trade and other countries' economies are also worth considering to provide a reference for international managers. Besides, joint emission reduction is also a topic worthy of in-depth study in the future to better guide carbon emission mitigation.

5. Conclusion

This study aims to quantify carbon emission effects embodied in the economic production chain and constructs three indicators (i.e., total emission effect, pull-type effect, and push-type effect) based on the network analysis approach. By applying these three indicators, the emission effects of 42 sectors in China are explored. (i) The total emission effects of sectors in China are quite different. Production and distribution of electric power and heat power have the strongest total emission effect, almost four times that of the second-ranked Construction. However, the effects of some sectors are very small and almost negligible. (ii) The pull-type effect and the push-type effect of high-emission sectors are very different. That is, the Production and distribution of electric power and heat power are dominated by the push effect, and priority should be given to improving its carbon emission intensity. While Construction is dominated by the pull effect and controlling its demand is more beneficial to emission reduction.

CRedit authorship contribution statement

Lijuan Xia: Conceptualization, Methodology, Formal Analysis, Writing - Original Draft. **Yongli Li:** Supervision, Validation, Writing - Review & Editing. **Xiao Chen Ma:** Data Curation, Writing - Review & Editing. **Yongli Li:** Supervision, Validation, Writing - review & editing. **Xiao Chen Ma:** Data curation, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

I have shared the data link in the manuscript.

Acknowledgments

This work is supported by the National Natural Science Foundation of China [72171059, 71771041], the Fundamental Research Funds for the Central Universities [FRFCU5710000220] and the Natural Science Foundation of Heilongjiang Province, China [No. YQ2020G003].

References

- Ali, Y., 2015. Measuring CO₂ emission linkages with the hypothetical extraction method (HEM). *Ecol. Indic.* 54, 171–183.
- Hickman, R., Ashiru, O., Banister, D., 2010. Transport and climate change: Simulating the options for carbon reduction in London. *Transp. Policy* 17 (2), 110–125.
- Hong, C., Zhao, H., Qin, Y., Burney, J.A., Pongratz, J., Hartung, K., Davis, S.J., 2022. Land-use emissions embodied in international trade. *Science* 376 (6593), 597–603.
- Jia, N., Gao, X., An, H., Sun, X., Jiang, M., Liu, X., Liu, D., 2020. Identifying key sectors based on cascading effect along paths in the embodied CO₂ emission flow network in Beijing-Tianjin-Hebei region, China. *Environ. Sci. Pollut. Res.* 27 (14), 17138–17151.
- Jiang, M., An, H., Gao, X., Zheng, H., Li, Y.u., 2021. Identifying the key sectors in the carbon emission flows along the production chain paths: A network perspective. *Ecol. Ind.* 130, 108050.
- Kumar, A., Abirami, S., 2018. Aspect-based opinion ranking framework for product reviews using a Spearman's rank correlation coefficient method. *Inf. Sci.* 460, 23–41.
- Li, Y.L., Chen, B., Chen, G.Q., 2020. Carbon network embodied in international trade: Global structural evolution and its policy implications. *Energy Policy* 139, 111316.
- Ma, N., Li, H., Tang, R., Dong, D., Shi, J., Wang, Z., 2019. Structural analysis of indirect carbon emissions embodied in intermediate input between Chinese sectors: a complex network approach. *Environ. Sci. Pollut. Res.* 26 (17), 17591–17607.
- Sanches-Pereira, A., Tudeschini, L.G., Coelho, S.T., 2016. Evolution of the Brazilian residential carbon footprint based on direct energy consumption. *Renew. Sustain. Energy Rev.* 54, 184–201.
- Wang, Y., Lei, Y., Fan, F., Li, L.I., Liu, L., Wang, H., 2021. Inter-provincial sectoral embodied CO₂ net-transfer analysis in China based on hypothetical extraction method and complex network analysis. *Sci. Total Environ.* 786, 147211.

- Xi, X., Zhou, J., Gao, X., Liu, D., Zheng, H., Sun, Q., 2019. Impact of changes in crude oil trade network patterns on national economy. *Energy Econ.* 84, 104490.
- Xia, F., Zhang, X., Cai, T., Wu, S., Zhao, D., 2020. Identification of key industries of industrial sector with energy-related CO₂ emissions and analysis of their potential for energy conservation and emission reduction in Xinjiang, China. *Sci. Total Environ.* 708, 134587.
- Zhang, Q., Jiang, X., Tong, D., Davis, S.J., Zhao, H., Geng, G., Guan, D., 2017. Transboundary health impacts of transported global air pollution and international trade. *Nature* 543 (7647), 705–709.