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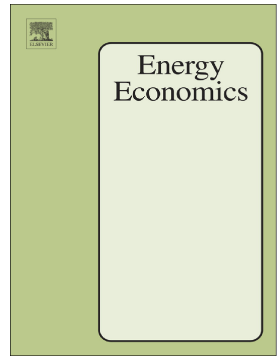

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Maximizing the effectiveness of carbon emissions abatement in China across carbon communities

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Abstract

The invisible and complex transfer of embodied carbon emissions makes the traditional production or consumption approach insufficient to inform emissions abatement actions because carbon communities have emerged during the transmission procedure of embodied carbon emissions. The carbon community—a group of sectors with more intensive embodied carbon emissions trades within the group than outside—provides the missing critical information about carbon abatement beyond the commonly used production and consumption approaches. This research aims to detect the carbon communities and examine the effect of community structure on sectors' direct carbon emissions. Unlike the industrial agglomeration in traditional economics and management studies, where the border is predefined in a geographical or administrative region, the hybrid input-output analysis and network analysis method detects the carbon communities data-driven, focusing on the embodied carbon emissions trades. Moreover, the hierarchical linear model examines the effect of community structure on sectors' direct carbon emissions to inform climate change policy-making and planning. The findings suggest around 19 carbon communities existing in China, which can advise local governments on their external cooperation strategies for a synergy. In addition, the regression results indicate that the increasing size and density of carbon communities can help mitigate sectors' direct carbon emissions.

Keywords

carbon emissions; transmission; network analysis; input-output analysis; community; industrial agglomeration

1. Introduction

The invisible and complex transfer of embodied carbon emissions is one of the main challenges for China to achieve its carbon peak and neutral goals (Duan et al., 2018; Mo et al., 2018). When the products of a sector are used by another sector, the carbon emissions produced by the first sector are transferred to the second sector in an embodied form. While the world economy and the domestic market in China have grown, the linear relationship between industries has been replaced by vertical, horizontal, and multi-lateral connections (Wu et al., 2021; Zhao et al., 2021). The complexity makes the assessment of critical sectors and regions that are responsible for emissions particularly difficult. The commonly used production-based and consumption-based accounting methods (Yang et al., 2021) focus on the beginning and the end of the supply chain system, while overlooking a large number of sectors participating in the transmission of emissions.

A transmission perspective can offer new insights for climate change policy-making by putting more pressure on sectors up and down the supply chains. Unlike the production and consumption perspective, which assigns the emissions abatement responsibilities to a few important sectors, the transmission perspective values the collective efforts of all the sectors in the economy. Adopting a transmission perspective requires a deeper focus on what happens between the production of goods and services where fossil fuels are burnt and their final consumption. All sectors of the economy along the transmission procedure can be scrutinized, and the collective effort across all sectors of the economy is encouraged to pursue deeper carbon abatement. The transmission perspective has emerged as an important research topic (Hanaka et al., 2017; Li et al., 2017; Liang et al., 2016). Recent attempts have been made to identify the critical sectors or clusters of sectors to use as leverage points for effective emissions abatement (Huang et al., 2019; Kagawa et al., 2015; Liang et al., 2016, 2015). In addition, some studies examined the effect of a sectors' transmission-related characteristics on emissions (Jiang et al., 2019; Wang et al., 2017).

The carbon community concept is a better tool for materializing the transmission perspective but has rarely been implemented in studying China's emissions. The carbon community is a group of sectors with much more intensive embodied carbon emissions trades within the group than outside. This ‘carbon community’ concept is similar to the ‘cluster’ concept in input-output analysis (IOA), which identifies the critical clusters of sectors along the transmission to leverage carbon abatement efforts (Kanemoto et al., 2018). However, the IOA- based clusters are identified alongside the pre-defined supply chain, usually with a pre-defined number of sectors in each cluster. In contrast, the carbon community is detected data-driven based on the embodied emissions transmission procedure within the whole economy. Almost all the sectors are grouped into communities. In addition, for the current research examining the effect of the embodied emissions transmission characteristics on sectors' direct carbon emissions, only the transmission structure characteristics at the sector level were considered (Jiang et al., 2019; Wang et al., 2017).

The carbon community can be viewed as a form of industrial agglomeration where many industries are geographically concentrated. While industrialization and urbanization have been progressing rapidly in China, industrial agglomerations have emerged, and their impacts on climate change are studied in-depth to inform policy-making and planning (Wang and Wang, 2019; Zheng et al., 2017). Unlike the traditional industrial agglomeration, which is usually pre-defined in a geographical or administrative region such as the Beijing-Tianjin-Hebei area, the carbon community is detected data-driven from the whole Chinese economy perspective. For example, we have detected the carbon communities in the embodied carbon emissions network in 2012 and found that the 30 sectors of Beijing were separated into six carbon communities of 10 provinces. Thus, the identified carbon communities can tell the closely connected sectors of provinces in terms of embodied carbon emissions trades, which can be targeted together by relevant policies for synergistic effects.

Our research contributes to the literature in the following ways. First, this study is among the first to introduce the hybrid method of network analysis and input-output analysis to reveal embodied carbon emissions transmission patterns and examine the effect of sectoral interdependence on carbon emissions from a meso perspective. Compared with input-output analysis, network analysis is more from a system-wide view and can provide the research result easy-to-understand and visually appealing. Secondly, this research applied the community concept in China by province and by sector. Unlike the cluster of sectors identified alongside the pre-defined supply chain or the industrial agglomeration pre-defined in a region (Kanemoto et al., 2018; Wang and Wang, 2019; Xu et al., 2018), we detect the carbon communities where sectors have intensive embodied carbon emissions trades data-driven with no pre-assumption. The research results will inform China's carbon emission policies at the national, provincial and sectoral levels. Thirdly, the research examines the effect of community structure on sectors' direct carbon emissions, which were seldomly discussed in previous studies. The research results can advise how to leverage the community structure on emissions abatement efforts.

This paper is built on our previous work, *Carbon Communities and Hotspots for Carbon Emissions Reduction in China* (Huang et al., 2019). We have accomplished a large amount of work to conduct further research and offer new insights. In this new research, the focus is to reflect the dynamics of carbon communities from 2007 to 2012 and examine the effect of community structure on sectors' direct carbon emissions. In contrast, our previous paper focused on a descriptive study of the embodied carbon emissions network in 2012. In addition, a new community detection algorithm is introduced in our current work to ensure the robustness of the carbon community division results. The paper is structured as follows. Section 2 introduces methods and data sources used in the research. Section 3 and section 4 provide results and discussion of this empirical study. Finally, section 5 concludes with policy suggestions and future studies.

2. Materials and methods

2.1 Methods

Environmentally extended input-output analysis (EE-IOA), network analysis, and statistical analysis are adopted in the research. EE-IOA is used to provide the information on the embodied carbon emissions flows among sectors of regions. On this basis, network analysis offers the toolbox to examine the embodied carbon emission from macro and meso perspectives. Moreover, statistical analysis is used to research how the embodied emissions transmission-related characteristics may influence sectors' direct emissions.

2.1.1 Embodied carbon emissions network construction

EE-IOA model lays the groundwork for the embodied carbon emissions network. The Leontief inverse matrix $\boldsymbol{L} = (\boldsymbol{I}-\boldsymbol{A})^{-1}$ reflects the direct and indirect input requirements of sector's outputs from other sectors(Leontief, 1970). Complemented with the carbon intensity information of each sector, the embodied carbon emission flows transmitted amid sectors can be outlined by matrix $\boldsymbol{G} = \widehat{\boldsymbol{k}}\boldsymbol{L}\widehat{\boldsymbol{f}}$, where $\boldsymbol{k}$ is the carbon emission intensity vector, $\boldsymbol{L}$ is the Leontief inverse matrix, and $\boldsymbol{f}$ is the final demand vector (Lenzen et al., 2012; Wiedmann et al., 2015). Detailed formula derivation and the embodied carbon emissions network construction steps can be found in our previous work (Huang et al., 2019). Each network is represented by $\mathbb{G}(N, L)$. For ease of expression, sector i in region r is referred as sector n, and sector j in region s is referred as sector m. The set of nodes is defined by vector $\mathcal{V}(N) = \{1,2,\cdots,N\}$, N= the sum of sectors within each region, and the set of directed edges is defined by the matrix $L = \{e_{nm} | n \rightarrow m, n, m \in \mathcal{V}(N), q_{nm} > 0\}$. The term q_{nm} denotes the quantity of embodied carbon emissions transferred from sector n to sector m.

Based on the raw embodied emissions network, network analysis algorithms and metrics are used to prevail the transmission pattern more clearly and systematically examine the transmission characteristics. The backbone of the raw emissions network is drawn out by using the network reduction algorithm proposed by Serrano et al.'s (2009) and a threshold of one tone (Huang et al., 2019). While noise in the raw network is significantly reduced to ensure the effectiveness of network algorithms and metrics, the essential multi-scale network structure is maintained in the backbone network. Moreover, network analysis metrics are used to examine the transmission pattern at the sector and community levels. In network theory, the changes in the topological structure of the underlying network have a critical influence on how the whole network will function or perform. In the context of this research, the structure of the embodied carbon emissions transmission network may affect sectors' carbon emissions.

2.1.2 Hierarchical linear model

Statistical analysis is adopted to measure the effect of transmission-related characteristics on sectors' carbon emissions. Structural decomposition analysis (SDA) is frequently used to analyze the overall change of the Leontief inverse matrix on carbon emissions. Though the Leontief inverse matrix reflects economic structure information from a macro perspective, a more systematic view is required to use the rich information provided by the matrix. Using statistical analysis, we can examine the influence of economic structure in more detail, especially from the community perspective. For example, the effect of community size on carbon emissions can be examined, which SDA analysis cannot reveal.

Embodied carbon emission networks have multi-level data structures. In these nested structures, the quantity of carbon emissions produced by a sector is influenced not only by the network structure at the individual sector level, but also by the community structure where the embodied carbon emissions trades were more intensive than outside, as shown in Figure1. The influence mechanisms at the node and community level interact and affect a sector's carbon emissions. For example, two sectors with the same values for transmission characteristics, such as the number of export partners, may have a different influence on emissions depending on their roles in their communities. At the same time, sectors that belong to the same community have the same community structure metric values, such as the community size.

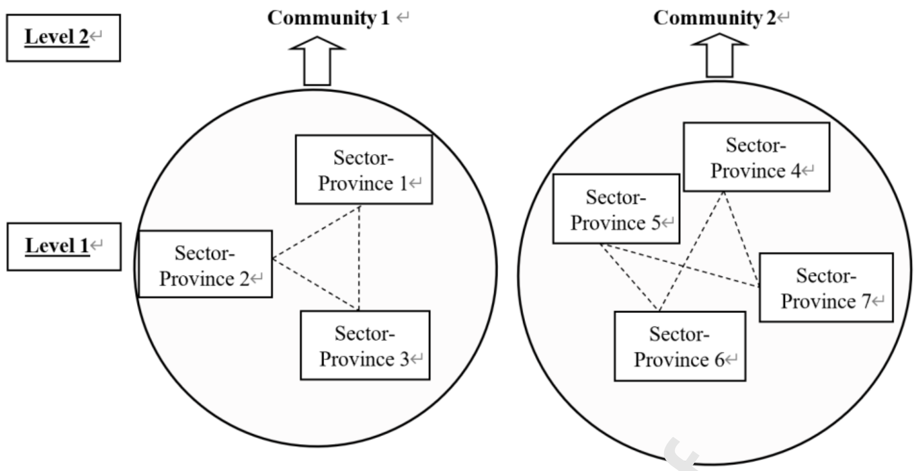

Figure 1. Multi-level data structure

This research adopts a hierarchical linear model to measure the effect of sector-level and community-level network structures on sectors' carbon emissions, as well as their interactions. The hierarchical linear model is widely used in management, education, and medical research (Bowers & Urick, 2011; Gentry & Martineau, 2010; Otaniet al., 2012; Zhang et al., 2018). It allows the individual-level variables to act on the outcome variable differently in each group by adding a random effect. During the estimation procedure, both the fixed effects at multiple levels and the heterogeneity of individual-level variables' influence are considered. Specifically, the heterogeneity is achieved by adding a random effect on the basis of fixed effect for the sector level network structure variables in the model.

The multi-level structure should be determined before constructing a hierarchical linear model. While the network structure at the sector node level is regarded as level 1, the community level is regarded as level 2. Moreover, for level 2, a time effect is added to communities. The data modelled in this study cover the years 2007, 2010, and 2012 and each sector belongs to a year-community. For example, the agriculture sector of Beijing in 2012 belongs to 2012-community 3, and its community ID is assigned as 2012_3. In this way, 2653 sectors are divided into 53 mutually exclusive year-communities. The details about the community division of sectors can be found in Appendix A.2. In addition, all the network structure variables are normalized in this study to avoid multi-collinearity and increase the model's interpretability.

Following the common practice adopted in the hierarchical linear models (Luke, 2004), four models were set up in the study.

Model (1). This is a random intercept model that contains only individual sector-level network structure variables as fixed effects. Because this study standardizes all the dependent and interpreted variables, there is no intercept term in the estimation equation. Models (2), (3), and (4) are treated in the same way. In addition, y_{ij} is the independent variable, referring to the carbon emissions (logarithm) produced by sector i of year-community j.

Level 1:

$$y_{ij} = \sum_{k=1}^{K} \beta_{k} \cdot Sector\_Level\_Features_{ijk} + \xi_{0j} + \varepsilon_{ij} \ , \ \varepsilon_{ij} \sim N(0, \sigma^2)$$
$$(\ i = 1, \ldots, 2653 \ , \ j = 1, \ldots, 53 \ ) \ (1)$$

Level 2:

$$\xi_{0j} = u_{0j} \ , \ u_{0j} \sim N(0, \tau_{00}^2) \ (2)$$

In these formulas, $Sector\_Level\_Features_{ijk}$ is the k-th sector-level network structure variable of sector i of year-community j. ξ_{0j} is a random variance difference between communities. ε_{ij} is the random error term of the model at the sector level, satisfying the homoscedastic assumption of statistical models. Model (1) does not include any independent variables at the year-community level, and all the information relevant to communities is attributed to the random term ξ_{0j}.

Model (2): This random intercept model includes sector- and community-level network structure variables as fixed effects. Based on Model (1), Model (2) adds network structure variables at the community level as fixed effects $\gamma_{\ell}(l = 1, \ldots, 4)$.

Level 1:

$$y_{ij} = \sum_{k=1}^{K} \beta_{k} \cdot Sector\_Level\_Features_{ijk} + \sum_{\ell=1}^{L} \gamma_{\ell} \cdot Community\_Level\_Features_{\ell} \ + \xi_{0j} + \varepsilon_{ij} \ ,$$
$$\varepsilon_{ij} \sim N(0, \sigma^2) \ , \ i = 1, \ldots, 2653 \ , \ j = 1, \ldots, 53 \ (3)$$

Level 2:

$$\xi_{0j} = u_{0j} \ , \ u_{0j} \sim N(0, \tau_{00}^2) \ (4)$$

The coefficients $\beta_{k}(k = 1, \ldots, 8)$ of sector-level network structure variables in both Model (1) and Model (2) do not change with the year-communities. In other words, the individual sector-level network structure influences a sector's carbon emissions in the same way in all year-communities.

Model (3): This random coefficient model includes sector- and community-level network structure variables. Based on Model (2), for the influence mechanism of sector-level structure on carbon emissions, a random term that varies with year-communities is added so that sector-level network structure influences a sector's carbon emissions differently in each year-community.

Level 1:

$$y_{ij} = \sum_{k=1}^{K} \beta_{kj} \cdot Sector\_Level\_Features_{ijk} + \sum_{\ell=1}^{L} \gamma_{\ell} \cdot Community\_Level\_Features_{\ell} \ + \xi_{0j} + \varepsilon_{ij} \ ,$$
$$\varepsilon_{ij} \sim N(0, \sigma^2) \ , \ i = 1, \ldots, 2653 \ , \ j = 1, \ldots, 53 \quad (5)$$

Level 2:

$$\beta_{kj} = \delta_{kj} + \epsilon_{jk}\ ,\ \epsilon_{jk} \sim N(0, \tau_{kj}^2)$$
$$\xi_{0j} = u_{0j}\ ,\ u_{0j} \sim N(0, \tau_{00}^2)\ (6)$$

In these formulas, the effect of the k-th sector level structure variable on carbon emissions is composed of a fixed part (δ_{kj}) and a random term (ϵ_{jk}). The former can be interpreted as the average effect of sector-level structure on carbon emissions, and the latter as a random effect which will be different for each year-community. This random term is introduced to take account of the heterogeneity of the impact of sector-level structure variables on carbon emissions, reflecting the multi-level structure of the data.

Model (4): Based on Model (3), Model (4) adds control variables to the model, reflecting the differences in sectors' economic characteristics, industrial production processes, and energy use.

When developing multi-level linear models, maximum likelihood estimation or restricted maximum likelihood estimation is generally used. There is not a significant difference in the values of the estimated coefficients between the two. The main difference is in the estimation of the variance part of the fixed effect and the random effect in the multi-level linear model. This study uses restricted maximum likelihood estimation, which is more common in the literature (Leeuw et al., 2008). 2.2 Data and variables

Energy consumption datasets, carbon emissions datasets, and the multi-region input-output (MRIO) datasets from the China Emission Accounts and Datasets (CEADs) (http://www.ceads.net) are used for this analysis. This empirical study looks closely at the transmission of the embodied carbon emissions from 2007 to 2012. These datasets are used to construct the embodied carbon emission transmission network and provide variables for the proposed hierarchical linear model. The MRIO tables of China for 2007, 2010, and 2012 are used to provide information on monetary flows between 30 sectors and 30 provinces in China. To match the sectors between the provincial-level CO_2 emission inventories and the China MRIO tables, sectors are aggregated or disaggregated. Please see Table A.1 in Appendix A in our previous work (Huang et al., 2019) for the sector matching details. The dataset consists of 30 sectors and 30 provinces after the matching process. In addition, the intervening period between 2007 and 2012 is a crucial period when China emerged as the world's manufacturing hub. Though there is a time lag, the research results can still provide insights into current policies.

2.2 Data and variables

2.2.1 Independent variables

This paper applies network analysis metrics to examine the embodied carbon emissions transmission procedure at both sector and community levels. The metrics are briefly introduced in table 1, and the detailed definitions and formulas are provided in Appendix A.1.

The multi-level modularity optimization algorithm is used to detect the carbon communities formed in the embodied emissions transmission procedure(Blondel et al., 2008). Additionally, to ensure robustness, the fast greedy modularity optimization algorithm proposed by Clauset (2004) was also applied to the network for community detection. Both algorithms do not pre-define the number of communities, and they are commonly used to discover communities in large complex networks (Bassett et al., 2011; Del Río-Chanona et al., 2017; Jia et al., 2018).

Metrics		Definition	Calculation	Interpretation
Community-level network structure variables				
Community size		The number of nodes contained in a community		The number of sectors contained in a community
Community density		The ratio of the existing edges to all possible edges in a community	$Density_j = \frac{l}{[n*(n-1)]/2}$	The ratio of the existing embodied carbon emissions trades to all possible trades
The community average path length		The expected number of edges between any pair of nodes in a community	$APL_j = \frac{1}{n\cdot(n-1)}\cdot\sum_{i\neq j} d(v_m, v_n)$	The expected number of embodied carbon trades between any two sectors in the community
Assortativity		The likelihood that nodes with high degrees tend to be connected with others with high degrees	$r_j = \frac{\frac{1}{\lvert D_j\rvert}\cdot\Sigma k_m k_n - \left[\frac{1}{\lvert D_j\rvert}\cdot\Sigma\frac{1}{2}\cdot(k_m+k_n)\right]^2}{\frac{1}{\lvert D_j\rvert}\cdot\Sigma\frac{1}{2}\cdot({k_m}^2+{k_n}^2) - \left[\frac{1}{\lvert D_j\rvert}\cdot\Sigma\frac{1}{2}\cdot(k_m+k_n)\right]^2}$	The likelihood that sectors with a large number of trade partners tend to be connected with each other
Sector-level network structure variables				
Degree Centrality	In-degree	The number of incoming edges to a node	$Degree_i^{in} = \sum_{i\neq j, i,j\in\mathcal{V}(N)} I[q_{ji} > 0]$	The number of a sector's import partner sectors on embodied emissions
	Out-degree	The number of outgoing edges from a node	$Degree_i^{out} = \sum_{i\neq j, i,j\in\mathcal{V}(N)} I[q_{ij} > 0]$	The number of a sector's export partner sectors on embodied emissions
Strength Centrality	In-strength	The weights assigned to all the incoming edges to a node	$Strength_i^{in} = \sum_{i\neq j, i,j\in\mathcal{V}(N)} q_{ji}$	The amount of embodied emissions a sector imports from others
	Out-strength	The weights assigned to all the outgoing edges from a node	$Strength_i^{out} = \sum_{i\neq j, i,j\in\mathcal{V}(N)} q_{ij}$	The amount of embodied emissions a sector exports to others
Closeness Centrality	Closeness-up	The distance between a node as the end and others nodes as starts	$ClosenessUp_i = f\cdot\left(\sum_l^\infty A^l\right)\cdot J_i := fTJ_i\mathbb{Y}$	The total weights of the carbon emission transfer paths ending in a sector

		based on the shortest path		
	Closeness-down	The distance between a node as the start and others as the ends based on the shortest path	$ClosenessDown_i = f \cdot J_i \cdot \left(\sum_{l}^{\infty} A^l\right) = fJ_iT\mathbb{Y}$	The total weights of the carbon emission transfer paths starting in a sector
Clustering Coefficient		The likelihood that the neighbors of a node are connected	$CC_{\mathbb{G}(i)} = \frac{\#\{jk \mid k \neq j, j \in N_{\mathbb{G}(i)}, k \in N_{\mathbb{G}(i)}\}}{d_{\mathbb{G}(i)}(d_{\mathbb{G}(i)} - 1)/2}$	The likelihood that the trade partners of a sector are also trade partners themselves
Betweenness Centrality		The total amount of flows going through a node	$b_i = fTJ_iTy$ * Details can be found in Liang's (2016) research.	The total quantity of embodied emissions flows passing a sector from all others

Table1 Network metrics in the context of carbon emissions transfer network

2.2.2 Dependent variable and other control variables

The dependent variables of the model are the quantities of carbon emissions directly produced by each sector in 2007, 2010, and 2012 (in thousands of tons). Figure 2 shows that the carbon emissions of various sectors each year have a highly skewed distribution. Therefore, this study performs a logarithmic transformation of the dependent variables (see Figure 3), adjusting the data to align with the statistical model assumptions.

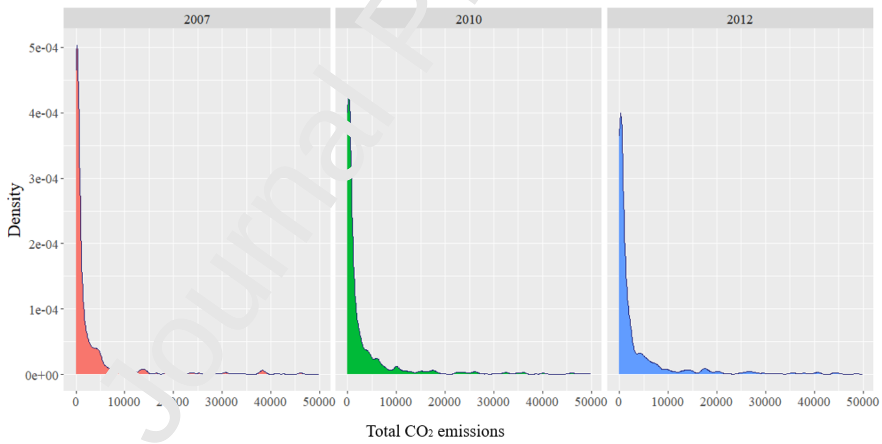

Figure 2 Probability density distribution of direct carbon emissions in 2007, 2010 and 2012

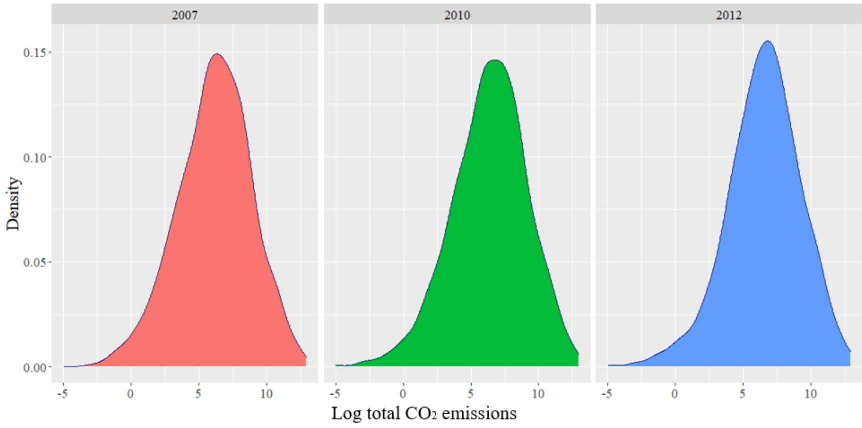

Figure 3 Probability density distribution of direct carbon emissions in 2007, 2010 and 2012 (Logarithmic transformation)

2.2.3 Other control variables

The data used in this study covers the three years of 2007, 2010, and 2012. Because the Chinese economy developed fast during this period, the effect of time on the relationships between structure variables on carbon emissions is considered in this research. Therefore, this study introduces two time-effect dummy variables:

$$Year\_2010 = \begin{cases} 1, \text{if from the year 2010 data} ; \\ 0, \text{if not from the 2010 data} ; \end{cases}$$

$$Year\_2012 = \begin{cases} 1, \text{if from the year 2012 data} ; \\ 0, \text{if not from the 2012 data} ; \end{cases}$$

Because the sector's characteristics may impact its carbon emissions, they are also taken as control variables in this study. Two dummy variables are introduced that characterize the nature of the sector, whether it belongs to the primary sector, manufacturing sector, or service sector:

$$Sector\_Indus = \begin{cases} 1, \text{if it is a manufacturing sector;} \\ 0, \text{if else} ; \end{cases}$$

$$Sector\_Serv = \begin{cases} 1, \text{if it is a service sector} ; \\ 0, \text{if else} ; \end{cases}$$

In addition, variables reflecting differences in economic characteristics, industrial production processes, and energy use are also introduced. To reflect a sector's economic features, its GDP, fixed capital depreciation, employee compensation, net taxes on production, and operating surplus are added to the model after logarithmic transformation. Furthermore, carbon emissions per unit of added value, and the ratio of intermediate input to final output, are added to the model as proxies for variations in production processes. In addition, to reflect a sector's preference in energy use, as coal is the primary energy type in China, the ratio of coal to all fossil fuels is used as a proxy for the sector's energy use structure.

3. Identification of carbon communities

3.1 Overview of the emissions transmission in China from 2007 to 2012

Three embodied carbon emissions networks are constructed to reveal the transmission procedure amid 30 sectors of 30 provinces in China from 2007 to 2012. Each network has 900 nodes representing provinces' sectors and has directed edges from 719,084 to 776,161, representing the transferred amount and direction of embodied carbon emissions. On this basis, the backbones of the three raw emissions networks are extracted to reveal the transmission patterns of embodied carbon emissions more clearly and to ensure the well-functioning of network metrics and algorithms. The robustness of the network reduction algorithm is checked by its application to the network data for the three years, 2007, 2010, and 2012, as shown in Table 2. The edges are dramatically reduced, with only about 7% of the raw network edges retained. However, more than 92% of embodied carbon emissions and multi-scale structural features are kept. The backbone network is characterized by scale-free, which has the presence of large hubs. In addition, a long-tail distribution can be observed for both network degree and strength, as presented in Figure 4.

Year		2007	2010	2012
Raw Network	Number of nodes	900	900	900
	Number of edges	719,084	776,161	774,391
	Total edges weights (Unit: thousand tonnes)	6,501,038.594	7,928,532.445	10,143,742.76
Backbonenetwork	Number of nodes	883	884	886
	Percentage of retained nodes	98.11%	98.22%	98.44%
	Number of edges	51,928	51,003	54,670
	Percentage of retained edges	7.22%	6.57%	7.06%
	Total edges weights (Unit: thousand tonnes)	6,019,726	7,376,856	9,428,826
	Percentage of retained edges weights	92.60%	93.04%	92.95%

Table 2 Raw network and reduced network comparison

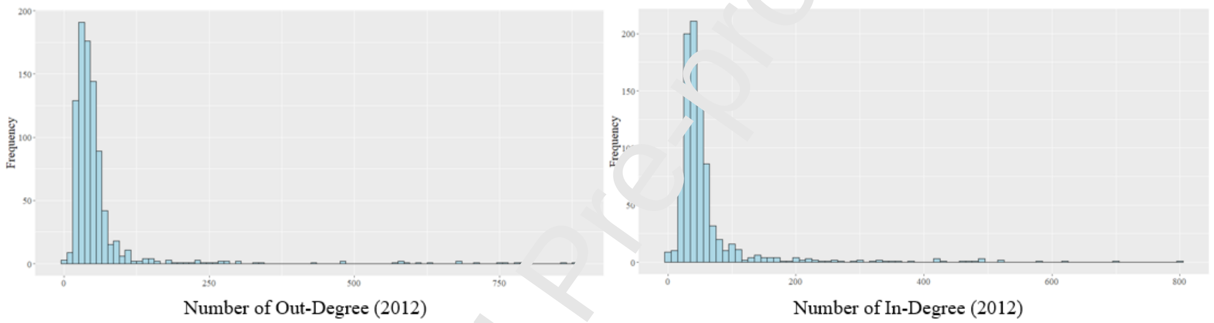

Figure 4. Degree and strength distribution of 2012 reduced embodied carbon emission network

Figure 5 presents the embodied carbon emissions transmission pattern at the national level from 2007 to 2012. In these networks, each node corresponds to a sector within a province. Sectors of the same province are put into the same color. The direction, color, and width of each edge represent the transmission direction, the province of the source sector, and the amount of the transmitted emissions, respectively. The sectors with intensive embodied carbon emissions trade are put nearby, while sectors with no trades are forced apart using the OpenOrd algorithm (Martin et al., 2011). From 2007 to 2012, the embodied carbon emissions were distributed unevenly among sectors of provinces. While clusters of sectors can be observed at the heart of the network, some isolated sectors are put on the periphery. In 2007, several components of provinces could be observed. Probably due to the shock of the financial crisis in 2008, the network became more separated in 2010. While the economy recovered, the network became more integrated in 2012, and a large component can be observed at the heart of the network.

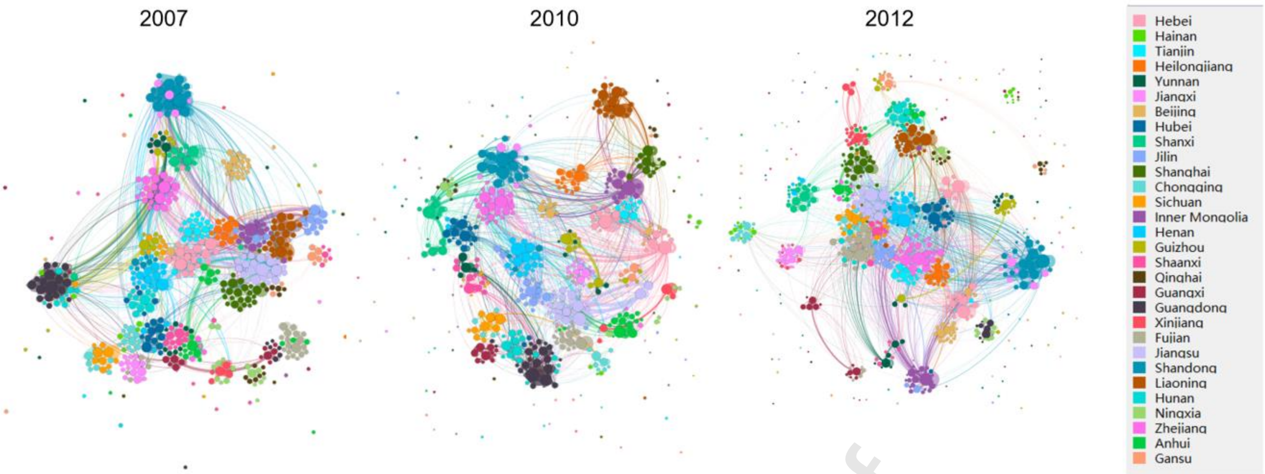

Figure 5. Embodied carbon emissions network from 2007 to 2012

The emissions transfer activities amid sectors of provinces were weakended by the 2008 global financial crisis, while the absolute amount of the transferred emissions increased steadily from 2007 to 2012. Four metrics were used to examine the network structure change in table 3. The average degree, which measures the number of direct trading partners of each sector, decreased by 1.9% from 2007 to 2010 and increased by 6.9% from 2010 to 2012. This result is consistent with the change in network density. The trading closeness of sectors in the emission network is measured by network density, which calculates the percentage of the actual trade relationships in the network to the number of all possible trade relationships in the network. The network density in 2007 was 0.067, which means that 6.7% of the possible trades existed in the actual network. This index decreased in 2010 and increased in 2012. The same trend can be observed in average path length and average clustering coefficient.

The embodied carbon emissions network is also characterized by "small world," suggested by a small average path length and a large average clustering coefficient. The small average path length indicates that any two sectors in the emissions network can be connected through a small number of edges. In addition, the high overall clustering coefficient means that a sector's transfer partner sectors are likely to transfer emissions directly between themselves. Finally, the small world characteristic suggests that the emissions can be easily transferred from a sector to others quickly.

Year	2007	2010	2012
Average degree (average number of each sector' trade partners)	58.809	57.696	61.704
Average path length (the minimum number of embodied carbon trades to connect any two sectors in the emissions network).	2.363	2.391	2.38
Average clustering coefficient (the probability that a sector' partner sectors have emissions transfer directly between the partners themselves)	0.377	0.397	0.378

Table 3 Network structure of embodied carbon emissions from 2007 to 2012

3.2 Carbon communities in China from 2007 to 2012

Carbon communities of sectors within provinces are outlined in the embodied carbon emissions network. In these carbon communities, the sectors have much more intensive embodied carbon emissions trades within their communities than outside. Multi-level modularity optimization algorithm(Blondel et al., 2008) and fast greedy modularity optimization algorithm (Clauset et al., 2004) are used to detect the carbon communities and ensure robustness. There are 17 communities detected in the year 2007 and 2010, and 19 communities in 2012. In addition, the percentage of carbon flows captured within a community out of total flows ranges from 50.05% to 98.05%. It suggests that each community has a fairly distinct boundary, because more than half of the embodied carbon emissions are kept within the boundary. At the same time, some communities still have extensive embodied emissions trades with outside sectors. Take the community of Tianjin-Beijing-Inner Mongolia community in 2012 as an example. While 56.24% of the embodied carbon emissions were captured, the community also had significant emission trades with Hebei, Shanxi, and Shandong.

The carbon communities generally formed within the traditional regional division in China from 2007 to 2012. Figure 6 presents the community detection result on the map of China. China is usually divided into six to eight regions (i.e., North, Northeast, East, Central, South, Southwest, and Northwest) in official channels. This regional division is also frequently used in academic papers analyzing the inter-regional carbon emissions transfer from a consumption perspective (Duan et al., 2018; Zhou et al., 2017). Thus, the carbon community detection results are consistent with the traditional wisdom. In addition, the sectors within the same province are usually grouped in the same community.

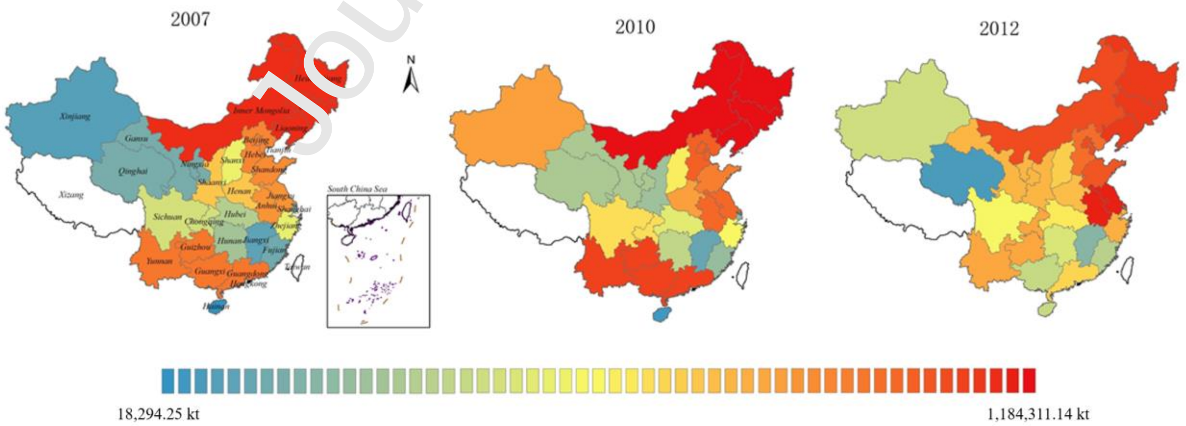

Figure 6 Community of provinces in the embodied carbon emissions network from 2007 to 2012
(Note: The same color is applied to the sectors within the same community.)

However, there is more than one carbon community within one region. Therefore, different targeted policies can be set for the carbon communities with the same region. For example, the northeast region consists of Inner Mongolia, Liaoning, Jilin, Heilongjiang. These four provinces were nearby geographically and traditionally had intensive trades with each other. From the community detection results, these four provinces were put into the same community in 2007 and 2010. However, while Inner Mongolia had more carbon-intensive trade with Tianjin and Beijing, such as through the electricity sector, Inner Mongolia moved to a new community with Tianjin and Beijing in 2012. Therefore, low-carbon strategies with different focuses should be applied to the provinces within the same region in 2012.

The majority of the provinces stayed in the same community throughout the three years. It was worth noting that while the 30 sectors of Beijing were put into six communities in 2012, while Beijing was put into the same community with Tianjin and Hebei in 2007 and 2010. In addition, the amount of in-flow was much more than outflow. It suggested that Beijing had a massive demand for goods and services and became increasingly interconnected with other provinces regarding the embodied carbon emissions transfer. Thus, though Beijing did not directly produce much carbon emissions, ranked the 3rd among 30 provinces in 2012, it indirectly consumed a considerable quantity of emissions from others.

Figure 7 visualizes the embodied carbon emissions flows amid carbon communities from 2007 to 2012. Each node represents a carbon community, and the node's size depends on the amount of embodied carbon emissions captured within it. Each edge's direction, color, and width represent the transmission direction, the source community, and the amount of the transmitted emissions, respectively. From 2007 to 2012, the number of communities increased from 17 to 19, and the embodied carbon emissions transmitted among communities became increasingly active during this period. In addition, the carbon communities which have more intensive embodied carbon trades are put in the center of the network, and the ones with fewer trades are placed on the periphery. Thus, communities' positions were in a dynamic procedure from 2007 to 2012, reflecting the dramatic changes in the trades in China.

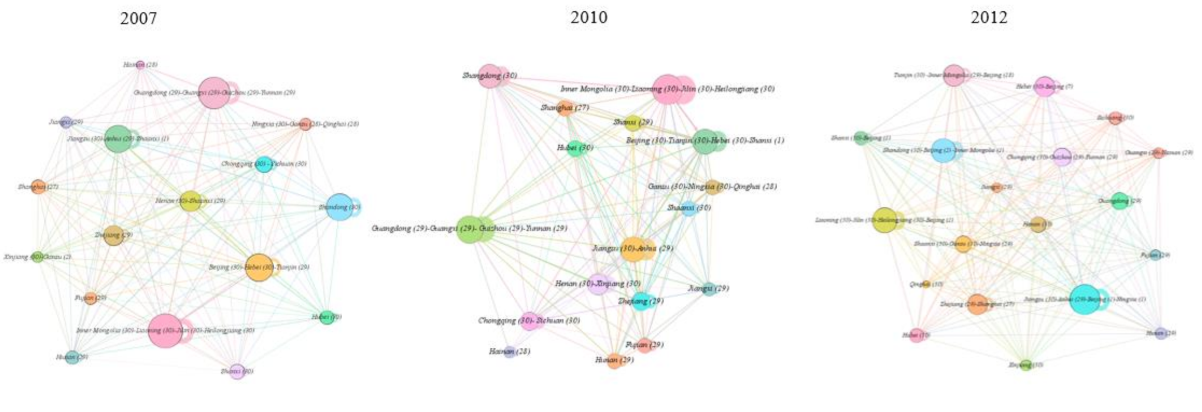

Figure 7 Visualization of communities in the carbon networks from 2007 to 2012

Two frequently used community detection algorithms in large networks are applied in this research to check the sensitivity of community division results to algorithms. Uncertainty may arise during the community detection procedure, whether the communities of sectors are outlined differently due to different algorithms applied to the networks. Both multi-level modularity optimization and fast greedy modularity optimization algorithms are based on modularity optimization, aiming to find the communities with the most distinct boundaries, with no assumption of the number and size. However, while the multi-level modularity optimization algorithm is a heuristic method, the fast greedy modularity optimization algorithm is a hierarchical agglomeration algorithm.

The change of community detection algorithms does not affect the community significantly, and the community detection result is robust. The variation of information (VI) and adjusted rand index are introduced to evaluate the difference in community detection results (Hubert and Arabie, 1985; Meilă, 2003). The more similarity the two community structures share, the less the VI is and the higher the adjusted rand index is. Table 4 suggests that the community structure detected by the two algorithms has a high degree of similarity for the embodied carbon emissions network in the years 2007, 2010, and 2012.

Year	Variation of information (VI)	Adjusted rand index
2007	0.011 (6.7833)	0.998
2010	0.059 (6.7844)	0.981
2012	0.035 (6.786)	0.991

Table 4 Community detection result comparison

Note: the number in the bracket under VI measurement is the theoretical upper limit of the VI obtained from the underlying network.

Some scholars have attempted to outline industrial clusters based on input-output analysis. However, there are some differences between network analysis-based community detection algorithms and input-output analysis-based cluster detection algorithms. The primary difference lies in the perspective of how clusters/communities are approached. Take the cluster detection algorithm proposed by Kanemoto et al. (2018) and the multi-level modularity optimization algorithm (Blondel et al., 2008) used by the current research as an example. Kanemoto et al. (2018) stated that the "clusters" should be sub-groups alongside the pre-defined supply chain. In contrast, the community detection algorithm takes communities as condensed sub-groups detected in the whole network without looking in detail at each supply chain. More specially, differences can be found in the objective function, optimization algorithms, assumption of community size, and the input treatment. Details are listed in table 5.

	Cluster detection algorithm by Kanemoto et al. (2017)	Community detection algorithm by Blondel et al. (2008) and two-step reduced network
Objective function	Minimize the normalized cut functions,	Maximize network modularity, aiming to find the

	aiming to detect clusters with the least inter-clusters connections along supply chains.	communities that have the largest overall modularity from the whole network perspective
Optimization algorithms	Greedy, hierarchical, and move based algorithms	Heuristic algorithm
Cluster/community assumption	Pre-define the cluster size, which is seven sectors in each cluster	No assumption about the size and number of communities
Treatment of input	Whole dataset of the input-output table	Two-step reduced network as input to reduce noise in the process of the community detection

Table 5 Comparison between cluster detection method and community detection method

Compared with Kanemoto et al. (2018)'s cluster detection method, the multi-level modularity optimization algorithm used by this research is more data-driven and more suitable in this research context. Our method does not pre-define supply chains and the community size. In addition, the community is detected based on the whole network, and almost all the sectors of provinces are grouped into communities instead of only focusing on the small critical clusters of seven sectors. The result can provide more insight for a synergistic effect among all sectors of provinces in China. In addition, our research extracts the backbone of the raw network, and it reduces noise in the process of community detection and has much less computation demand.

4 The effect of carbon communities' structure on emission changes

4.1 Statistics summary and multi-level analysis

Figure 8 shows the probability density distribution of sectors' carbon emissions in logarithmic form for each year-community. The panels are sorted by the order of community number and by year. Significant differences can be observed for the distribution of each year-community. Take distribution of community 1 in 2007 (panel 2007_1), 2010 (panel 2010_1), and 2012 (panel 2012_1) as an example. Though they generally follow a normal distribution, there were two peaks in 2007, one relatively high peak in 2010, and no significant peak but a wide value range of direct carbon emissions in 2012. By adopting a multi-level linear model, the differences in each year-community are considered, thereby reducing estimation bias.

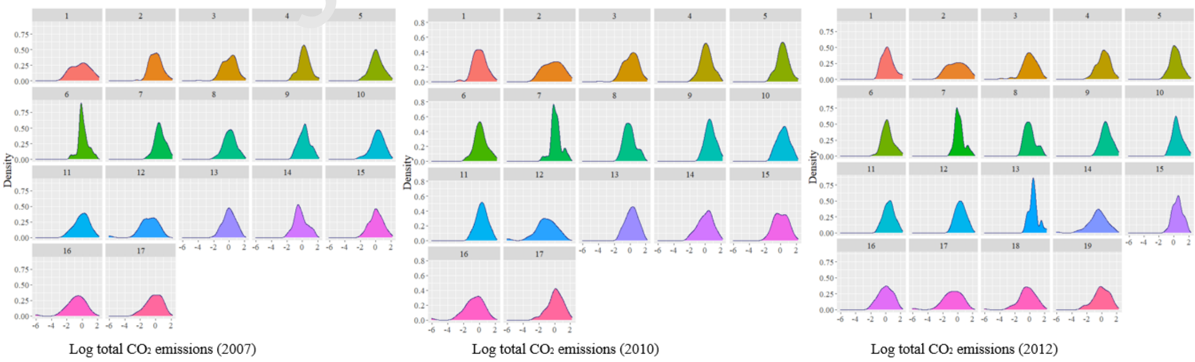

Figure 8 Probability density of sector carbon emissions for each year-community in 2007, 2010 and 2012

Table 6 gives descriptive statistics for network structure metrics at the sector and community levels. Due to different measurement units, the differences in the range of variables are large. In addition, there are significant imbalances in the distributions of variables, which can be observed in the values of skewness and kurtosis. Consequently, this study standardizes all explanatory variables to improve reliability.

	Minimum	mean	maximum	S.D	Skewness	Kurtosis
<u>Individual level characteristics</u>						
In-degree	0	59.66	797	73.253	4.894	33.097
Out-degree	0	59.63	877	93.946	5.833	40.745
In-strength	0	8603.6	263668.1	19094.51	5.065	39.45
Out-strength	0	8603.6	477974.0	32633.23	7.607	74.773
Clustering coefficient	0.2334	0.7957	1.1923	0.133	-1.146	4.615
Upward closeness	0	6896.7	229363.7	16958.18	5.314	41.305
Downward closeness	0	6895.2	375653.2	26786.03	7.572	75.033
Betweenness	0	10084.1	369085.9	23892.76	6.386	63.58
<u>Group level characteristics</u>						
Size	27	66.58	170	32.985	0.249	1.677
Density	0.207	0.446	0.854	0.207	0.563	1.733
Average path length	0.011	0.477	3.343	0.586	3.329	14.614
Assortativity	-0.097	-0.048	0.030	0.030	0.326	2.307

Table 6 Descriptive statistics of the network structure variables (original values)

Table 7 gives the partial correlation coefficients of each network structure variable to determine whether the model has an obvious multi-collinearity problem. The correlation between structure variables at the community level is relatively high because sectors of the same community have the same values of community network structure variables. This collinearity problem can be solved using the hierarchical linear model, which considers the objects in the same group to share variance according to their common group characteristics. The absolute values of the other network structure variables at the sector and community levels are all less than 0.5, indicating a weak correlation, except for the correlation between degree and strength. On the other hand, the coefficients between out-degree and out-weight, in-degree and in-weight are higher than 0.8, indicating a strong correlation. In addition, by including out-strength as an independent variable, endogeneity is a potential concern. This is mainly because both the dependent variable, i.e., a sector's direct carbon emissions, and out-strength, i.e., the amount of embodied carbon emissions that a sector transmits outward, are determined or partly determined by a sector's economic output and carbon emissions intensity.

	Out-degree	**In-degree**	**Out-strength**	**In-strength**	**Clustering coefficient**	**Closeness-Up**
Out-degree	-					

In-degree	-0.048***	-				
Out-strength	0.893***	-0.035*	-			
In-strength	0.123***	0.823***	0.153***	-		
Clustering Coefficient	-0.576***	-0.407***	-0.484***	-0.450***	-	
Closeness-up	0.100***	0.410***	0.121***	0.405***	-0.113***	-
Closeness-down	0.449***	0.027	0.447***	0.132***	-0.377***	0.275***
Betweenness	0.312***	0.224***	0.313***	0.282***	-0.237***	0.369***
Size	0.023	-0.005	-0.028	-0.069***	-0.007	-0.132***
Density	-0.026	0.018	0.042**	0.101***	0.017	0.170***
APL	0.014	0.037*	0.069***	0.145***	-0.036**	0.081***
Assortativity	-0.009	0.123***	0.058***	0.158***	-0.032*	0.195***

	Closeness-down	**Betweenness**	**Size**	**Density**	**APL**	**Assortativity**
Closeness-down	-					
Betweenness	0.270***	-				
Size	-0.072***	-0.140***	-			
Density	0.142***	0.213***	-0.888***	-		
APL	0.162***	0.180***	-0.343***	0.356***	-	
Assortativity	0.173***	0.265***	-0.711**	0.720***	0.393***	-

Table 7 Partial correlation coefficient matrix of structural characteristics of China's carbon emissions transfer network (original variables)

Note: ***, **, and * indicate that results are at 1%, 5%, and 10% significance levels, respectively; closeness-up, closeness-downward, and betweenness are logarithmically transformed values.

This study uses the relative out-degree and relative out-strength as independent sector-level network structure variables rather than absolute values to deal with the high correlation between degree and strength and the potential endogeneity problem. Specifically, for sector i, the relative out-degree and relative out-strength are defined as

$$Relative\ out-degree = {Degree_i^{out}}\Big/{Degree_i^{in}}$$

$$Relative\ out-strength = {Strength_i^{out}}\Big/{Strength_i^{in}}$$

Table 8 shows the partial correlation coefficients between variables after introducing the ratio variables. The partial correlation coefficients between sector-level and cross-level variables have decreased significantly and are less than 0.5, indicating a weak correlation. In addition, the high correlation between structure variables at the community level is solved by using the hierarchical linear model, which considers sectors in the same community to share common variance.

	Relative Out-degree	**Relative Out-Strength**	**Clustering coefficient**	**Closeness-Up**	**Closeness-down**	**Betweenness**
Relative Out-degree	-					

Relative Out-strength	0.081***	-				
Clustering coefficient	-0.200***	-0.076***	-			
Closeness-Up	-0.477***	-0.291***	-0.113***	-		
Closeness-down	0.100***	0.079***	-0.377***	0.275***	-	
Betweenness	-0.130***	-0.014	-0.237***	0.369***	0.270***	-
Size	0.072***	0.023	-0.007	-0.132***	-0.072***	-0.140***
Density	-0.067***	-0.021	0.017	0.170***	0.142***	0.213***
APL	0.009	-0.003	-0.036**	0.081***	0.162***	0.180***
Assortativity	-0.053***	-0.021	-0.032*	0.195***	0.173***	0.265***

	Size	**Density**	**APL**	**Assortativity**
Size	-			
Density	-0.888***	-		
APL	-0.343***	0.356***	-	
Assortativity	-0.711***	0.720***	0.393***	-

Table 8 Partial correlation coefficient matrix of topological characteristics of China's carbon emissions transfer network

Note: ***, **, and * refer to significance levels of 1%, 5%, and 10%, respectively; closeness-up, closeness-downward, and betweenness are logarithmically transformed values.

The multi-level nested data structure is verified before moving on to applying the hierarchical linear model. As presented in Table 9, three indexes are commonly used to determine whether data is in a multi-level structure and whether it is necessary to use a hierarchical linear model. ICC(1) measures the extent to which the effect variance of sector-level structure variables can be explained by community membership (Raudenbush and Bryk, 2002). ICC(2) measures the reliability of the mean values of each community (Bliese et al., 2002), and it is affected by ICC(1) and the community size. The $r_{wg(j)}$ agreement index measure the interchangeability of individual sector's response among communities. The higher the $r_{wg(j)}$ value is, the lower the interchangeability is, indicating greater difference in one community member's response to another community member's response (Klein and Kozlowski, 2000). The three indexes range from 0 to 1. The larger the coefficient, the greater the need to use a hierarchical linear model. For the sector-level network structure variables, as presented in Table 9, ICC (1), ICC (2), and $r_{wg(j)}$ values are all significantly non-zero, and in particular ICC (2) and $r_{wg(j)}$ have large values. Therefore, it is justified and reliable to adopt the hierarchical linear model in this study.

	ICC(1)	ICC(2)	$r_{wg(j)}$
Relative Out-degree	0.0146	0.4265	0.8783
Relative Out-strength	0.0018	0.0813	0.8958
Clustering Coefficient	0.0228	0.5386	0.4878
Upward closeness	0.0972	0.8435	0.6526
Downward closeness	0.1044	0.8537	0.5727
Betweenness	0.2140	0.9316	0.6629

Table 9 ICC (1), ICC (2) and $\boldsymbol{r_{wg(j)}}$ estimates of sector-level emissions network structure variables

Note: closeness-up, closeness-downward, and betweenness are logarithmically transformed values.

4.2 Regression results

Table 10 presents the estimates of the influence of China's embodied carbon emissions network structure on sectors' emissions in each of the four models. The empirical results confirm that the structure of the carbon communities had significant roles on the sectors' direct carbon emissions. From Model (1) to Model (4), the nested multi-level data structure for sector-level and community-level network structure variables have been verified. The fitting effect of the models has been significantly improved. While Model (1) only considers the sector-level transmission structure, the fitting effect of Model (2) has been increased ($\mathcal{X}^2 = 9.111$，$Pr(> Chisq) < 0.0584$) by adding the community transmission structure variables. Through taking account of the nested multi-level data structure, Model (3) allows the effect of the sector-level structure on emissions to differ in each year-community, and the fitting effect has been improved significantly ($\mathcal{X}^2 = 966.66$，$Pr(> Chisq) < 0.0000$). Model 4 further considers sectors' own characteristics, such as industrial production processes and energy use as control variables. Moving from Model (1) to (4), both AIC and BIC decrease significantly, indicating an improved model fitting effect.

	Dependent variable: sectors' production-based carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Fixed effect				
Community level characteristics				
Size		0.0252** (0.0122)	-0.0132 (0.0098)	-0.0199** (0.0099)
Density		0.0134 (0.0116)	-0.0120 (0.0097)	-0.0197* (0.0101)
Average path length		0.0094* (0.0049)	-0.0034 (0.0046)	-0.0056 (0.0045)
Assortativity		0.0059 (0.0073)	-0.0085 (0.0065)	-0.0130* (0.0068)
Sector level characteristics				
Relative Out-degree	0.0128* (0.0073)	0.0117 (0.0073)	-0.0414 (0.0391)	0.0451** (0.0187)
Relative Out-strength	0.0277*** (0.0065)	0.0288*** (0.0065)	1.2068*** (0.2208)	1.5889*** (0.2427)
Clustering Coefficient	-0.0795*** (0.0042)	-0.0796*** (0.0042)	-0.0736*** (0.0046)	-0.0573*** (0.0041)
Upward closeness	0.2028*** (0.0064)	0.2033*** (0.0064)	0.3709*** (0.0187)	0.2893*** (0.0168)
Downward closeness	0.9993*** (0.0069)	0.9992*** (0.0069)	1.0134*** (0.0097)	1.0163*** (0.0106)
Betweenness	-0.1545*** (0.0089)	-0.1564*** (0.0089)	-0.2488*** (0.0191)	-0.3061*** (0.0208)
Sector economic characteristics				
Compensation of employees				0.1117*** (0.0110)
Net taxes on production				0.0009

	Dependent variable: sectors' production-based carbon emissions (logarithmic)			
	(1)	(2)	(3)	(4)
				(0.0037)
Depreciation of fixed capital				-0.0583***
				(0.0082)
Operating surplus				0.0074**
				(0.0034)
Intermediate input/ final output ratio				0.0119***
				(0.0040)
Coal/total fossil fuel ratio				-0.0051*
				(0.0028)
Gross output				0.0608***
				(0.0131)
Time				
Year 2010	-0.0264**	-0.0267**	0.0214**	-0.0247**
	(0.0124)	(0.0121)	(0.0104)	(0.0108)
Year 2012	-0.0352***	-0.0316**	-0.0012	-0.0379***
	(0.0121)	(0.0119)	(0.0103)	(0.0114)
Sector				
Manufacturing sector	0.0139	0.014[illegible]	0.0480***	0.1345***
	(0.0087)	(0.[illegible]6)	(0.0115)	(0.0144)
Service sector	0.0391***	0.[illegible]392**	0.0470 ***	0.0892***
	(0.0116)	(0.01[illegible])	(0.0128)	(0.0154)
Random effects (variance)				
Relative Out-degree			0.0501 ***	0.0073***
			(87.168)	(34.831)
Relative Out-strength			1.6086***	2.2486***
			(85.310)	(42.987)
Clustering Coefficient			0.0003***	0.0002*
			(19.709)	(13.300)
Closeness-up			0.0140***	0.0109***
			(306.294)	(204.423)
Closeness-down			0.0028***	0.0037***
			(67.063)	(108.134)
Betweenness			0.0139***	0.0168***
			(298.257)	(407.311)
Model fitting information				
intra-class correlation (ICC)	0.021	0.018	0.989	0.993
AIC	-1438.91	-1406.68	-2332.11	-2623.15
BIC	-1368.31	-1312.545	-2079.121	-2328.98
Observed sample size	2,653	2,653	2,653	2,653

Table 10 Relationship between the embodied carbon emissions network structure and sectors' direct carbon emissions

Note: ***, **, and * indicate that the data are significant at 1%, 5%, and 10% levels, respectively, and the standard errors of the estimated coefficients are in parentheses.
For random effect (variance), the values in brackets are the likelihood ratio test statistics results.
Upward closeness, downward closeness, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus, and GDP are logarithmically transformed.

Once the regression models consider the multi-level structure, the carbon community structure plays a significant role in sectors' direct carbon emissions. In Model (2), although both the transmission characteristics at sector and community levels are considered, the multi-level data structure is not considered. In this case, the community-level structure variables have no statistically significant effect on emissions, except for the size of the community. Based on fixed effects, Models (3) and (4) allow the impact of sector-level structure variables on sectors' carbon emissions to differ in each community, reflecting the multi-level data structure. The empirical results confirm that the effects of transmission characteristics at the sector level are adjusted by their community structure, which is suggested by the significant random effects of sector-level transmission variables. In other words, the sectors with the same transmission characteristics at the sector level, such as the same number of embodied emissions trade partners, their impacts on sectors' direct carbon emissions differ in each community. Thus, it provides empirical evidence support for tailored policies to accommodate local needs.

When the scale of the community expands, and the embodied emissions trades get intensified, the carbon emissions directly produced by the sectors within the community decreases. When the multi-level structure is considered in Models (3) and (4), the regression coefficients of community size (the number of sectors contained in a community), community density (the ratio of the existing embodied carbon emissions trades to all possible trades), and assortativity (the likelihood that sectors with a large number of trade partners tend to be connected with each other) are significantly negative. When an existing community has more intensive trades of emissions with outside sectors, the size of the community grows. In addition, when the community density increases, there are more embodied emissions trades among sectors in a community. The increasing community scale and density can assist sharing of environmental protection facilities, energy-saving knowledge, and emission-reducing technology. Thus, the community of sectors can achieve scale effect, reduce carbon emission intensity, and encourage collective learning of upstream and downstream sectors in developing and utilizing low-carbon technology (Cohen et al., 2019).

The outlined carbon community can be regarded as a special form of industrial agglomeration, where industries are geographically concentrated. While industrial agglomeration is usually pre-defined in a geographical or administrative region such as the Beijing-Tianjin-Hebei area, the carbon community is detected data-driven from the whole Chinese economy perspective. The empirical research results are consistent with the existing research that the industrial agglomeration brought emission-reduction effect in China (Chen et al., 2018; Wang and Wang, 2019).

Moreover, when sectors with many trade partners get connected more with each other in a community, measured by assortativity, sectors' direct carbon emissions are more likely to be reduced. At the same time, the connectivity between any two random sectors in the economy in terms of the average minimum number of embodied emissions trades, measured by average path length, has no significant role in sectors' carbon emissions. It suggests that though embodied carbon emissions trades can reduce carbon emissions through collective learning and resource sharing, the reduction is more effective through the trade between a pair of sectors with many trade partners. Therefore, the connection between hub sectors in the embodied carbon emissions network needs to be paid close attention.

The embodied emissions transmission characteristics at a sector level also have significant effects on sectors' direct emissions. The sectors with more out-ward trade partners (measured by relative out-degree) and more considerable emissions embodied in outward trade (measured by relative out-strength) tend to have more direct carbon emissions. It is consistent with the fact that for the top sectors in terms of direct carbon emissions in China, such as the electricity sectors, most of their products are used by other sectors, resulting in large relative out-degree and out-strength. In addition, relative out-strength has a more significant effect on the increase in carbon emissions than relative out-degree. It is probably because the top sectors in terms of direct carbon emissions production are not always the ones that are critical in directly transmitting emissions to an extensive breadth of others.

The transmission hub sectors play a significantly negative role in their direct carbon emissions. The high-betweenness sectors are esteemed to be transmission hubs from a national perspective, with much embodied carbon emissions going through. In this process, the sectors with high betweenness do not 'produce' high carbon emissions by themselves. Instead, due to their broad transfer relationship, they directly and indirectly import a large number of emissions from other sectors, and this has the effect of reducing their direct emissions. Take the electricity sector of Beijing as an example, which reduces its direct carbon emissions through using electricity from other provinces such as Shanxi and Inner Mongolia provinces. Moreover, for sectors with high clustering coefficients, a large percentage of their embodied emissions trade partners are partners themselves. In other words, these sectors have formed an interconnected trade structure locally. This structure can enlarge the emissions reduction effect through the knowledge and resource sharing through upstream and downstream industries.

A sector's position along the embodied carbon emissions transfer paths also significantly affects its direct carbon emissions. The importance of sectors as carbon consumers is measured by closeness-up, which calculates the total carbon emissions along the transfer paths ending in a sector. The positive correlation coefficient suggests that the closer the sector is to the consumers' final demand, the sectors' carbon emissions increase. This increase is probably driven by the ever-growing Chinese consumers' final demand with the fast economic development, such as demand for more spacious apartments and more fine food. However, the importance of sectors as carbon consumers plays a much more significantly positive role, measured by closeness-down by calculating the total carbon emissions along the transfer paths ending in a sector. Take the electricity sector with high close-down as an example. The driving force coming from the downstream industries keeps these sectors' production of carbon emissions at a high level.

The empirical results of Models (1) to (4) show that compared to 2007, sectors' carbon emissions in 2010 and 2012 slowed down significantly. Many factors caused this decline in carbon emissions, but there were two main reasons. First, China is accelerating low-carbon development to tackle climate change. In the performance evaluation of local governments, indicators such as carbon emissions intensity reduction have been added to push the low-carbon transformation further. Secondly, the upgrading of industrial infrastructure and the increasing proportion of the economy occupied by service sectors also contribute to the decline in carbon emissions.

The sectors' production processes and economic characteristics also influence carbon emissions. The gross output of a sector plays a significant role in its carbon emissions. Compared with primary industries, being the manufacturing sector plays a significant part in sectors' direct emissions. In addition, the compensation of employees, net taxes on production, and operating surpluses all have significant positive impacts on sectors' carbon emissions. In contrast, the depreciation of fixed capital has a significant inhibitory effect. Moreover, industries with higher intermediate input/ final output ratios produce more carbon emissions. In addition, the proportion of carbon emissions that comes from coal use plays a marginally significant impact on carbon emissions. The result is probably because a reduction effect brought by non-fossil energy is not reflected in the percentage due to data unavailability. Additionally, the emission factor among all the 17 fossil energy types is similar, ranging from 0.06 Mt CO_2/PJ to 0.08 Mt CO_2/PJ, except for coke and natural gas, which is 0.10 Mt CO_2/PJ and 0.05 Mt CO_2/PJ. Thus, while fossil fuel consumption contributes to carbon emissions as the primary source, the percentage of coal out from all fossil fuels only plays a marginally significant role.

Two robustness checks are conducted to ensure the validity of the research results obtained by the hierarchical linear model. This first one is to test the temporal significance of the hierarchical linear model, which is tested by lagging one period of the sectors' carbon emissions. The effect of network structure on sectors' direct emissions may be subject to a time lag. Hence, this research explores the time lag effect of the network structure on sectors' emissions. In addition, due to data unavailability, this study keeps the same independent variables and explores their influences on sectors' carbon emissions in 2008, 2011, and 2013. The regression results presented in Appendix A.4 are consistent with Table 10, which indicates that the regression model is robust. Moreover, it demonstrates that the structure of China's embodied emissions network has a long-lasting and consistent impact on carbon emissions. Furthermore, regression in a yearly manner is conducted to check the stability of the embodied carbon emissions network structure's effect on sectors' carbon emissions. When all the data are pooled together with two time-effect dummy variables, the results in each year, presented in Appendix A.5, are consistent in the direction and scale of estimated coefficients.

5. Conclusion and policy implications

This study applied the community concept from network analysis to detect the carbon communities in China, where sectors have intensive embodied carbon emissions trades in the embodied emissions transmission procedure. Unlike the traditional economics and management perspectives, the carbon community is detected data-driven with no pre-assumption using the hybrid input-output analysis and network analysis. In addition, network visualization presents the transmission patterns of emissions visually appealing from a meso perspective. Moreover, the detected around 19 carbon communities in China can provide new insights on provincial governments' external collaboration. Unlike the input-output analysis-based cluster analysis identified along a pre-defined supply chain or industrial agglomeration studied in a pre-defined region, all the sectors of provinces are grouped into the 19 carbon communities in a data-driven way from the whole Chinese economy perspective. Finally, the effect of community structure on sectors' direct carbon emissions is examined by the hierarchical linear model to provide insights on climate change policy-making and planning.

The results demonstrate that communities of sectors have formed in the highly imbalanced embodied carbon emissions trade network, and they can be targeted for leveraging emissions abatement efforts. Because the embodied emissions trades are much more active within a community, targeting the sectors of the same community may result in a synergy. In addition, the community structure changes over time, which needs constant attention to provide practical guidance. Moreover, regression results suggest that the increasing expansion and density of a community can bring an inhibitory effect on sectors' carbon emissions. Furthermore, benefiting from pollution control resources sharing and the convenience of governmental regulation, the formation of communities can encourage low-carbon technology development and utilization, improve energy utilization efficiency, and thus reduce carbon emissions.

The analysis can imply the following policy suggestions.

First, to reduce the carbon emissions of a sector, the transmission characteristics of the sector and its community, which could be beyond the regional boundary, should be considered together. The transmission characteristics of emissions at sector-level and community-level interact with each other and affect sectors' carbon emissions together. Apart from the fixed effect of the transmission structure at the sector level on sectors' direct carbon emissions, there is also a significant random effect posed by their community structure. For example, the random correlation coefficient of relative out strength is more significant in Shanxi community than the average of all other communities. It suggests that the driving force of Shanxi's export partners is larger than the average on Shanxi sectors' direct carbon emissions. Therefore, more efforts should be made by Shanxi to identify the primary embodied carbon emissions partners to reduce carbon emissions effectively together. In addition, the trade partners ought to be considered for the communities with significant outside links, whose percentage of in-community carbon flows is relatively small. Take the Tianjin-Beijing-Inner

Mongolia community in 2012 as an example. The strong interactions with Hebei, Shanxi, and Shandong should not be missed for collaborative efforts.

Secondly, a community-specific policy is required for effective carbon emissions mitigation. The community detection results advise provincial governments to focus on carbon emission mitigation efforts for self-reformation or external collaboration. For communities consisting of only one province, such as Hubei community and Hunan community in the central part of China, the provincial governments should prioritize internal improvement. Because most of the embodied carbon emissions from production to consumption are captured within the provinces, the responsibility for emissions abatement rests mainly on the provincial governments themselves. In addition, the collaboration among provinces within the same community shall be promoted for a synergistic policy benefit for communities with more than one province. For example, cooperation among Liaoning, Jilin, and Heilongjiang provinces should be encouraged, which stay in the same community from 2007 to 2012.

Thirdly, the promotion of interaction among communities in these large components should also be taken into account. Policies should be developed to utilize the self-purification effect brought by communities fully. The inhibitory effect brought by the increasing expansion and density of a community can be targeted by promoting interactions among various sectors of provinces, such as establishing unified industry parks. In addition, one large component is emerging, with several communities overlapping with each other in the northern part of China from 2007 to 2012. As the Chinese economy develops and the sectoral interdependence intensifies, more large components may be observed in the future.

Last but not least, the developed hub cities in a community or communities should be highlighted in low-carbon economic development. The developed hub cities generally have a much more considerable amount of imported carbon emissions than exported due to industrial structure and technology advantages. They also become more integrated with sectors of other provinces as the economy grows. For example, while Beijing, Tianjin, and Hebei were in the same community in 2007, the sectors of Beijing were divided into six communities in 2012. Thus, these developed hub cities can pull the low-carbon transition for a large region through clear preference and requirement of low-carbon inputs along supply chains. In addition, the knowledge sharing of hub cities can have a far-reaching impact on these communities. As big data technology develops, more hub cities can be identified at a higher data resolution network in the future.

Our research was limited by data availability, especially due to the slow updating of MRIO tables. Therefore, the analysis could not be based on the latest sectoral emissions transmission data or long time series data in China. Nevertheless, the framework, models, metrics, and algorithms can be used more effectively once the data is made available. In the future, it will be possible to use this research as a basis to construct dynamic network models based on real-time emissions data at higher data resolution. In addition, due to the scope and resource limitation, we chose to focus on the internal effort of China for the current research. While the Chinese economy has been increasingly integrated with the rest of the world, more future efforts can be made from a global perspective to leverage the collective efforts to tackle global climate change together.

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Inclusion and Diversity:

The author list of this paper includes contributors from the location where the research was conducted who participated in the data collection, design, analysis, and/or interpretation of the work.

Appendix

Appendix A.1. Network structure variables

Community-level network structure variables

Community size. It is defined as the number of sectors contained within a community.

Community density. The density of a community refers to the percentage of the existing edges to all possible edges contained within a community (Newman, 2003). The greater the community density, the higher the ratio of actual edges to possible edges. For community j with n nodes in the carbon network, the community density is defined as:

$$Density_j = \frac{l}{[n*(n-1)]/2} \text{ Eq. (A.5)}$$

where l is the number of carbon emission transfer links actually observed in the community.

The community average path length. The community average path length (APL) measures the closeness of nodes in a community. The shorter the APL is, the closer the nodes in the community are. For any two nodes m and n in the network, the path length $d(v_m, v_n)$ between the two is defined as the number of edges on the shortest path from node m to n (Newman, 2003). Therefore, for community j, the average path length (APL_j) is equal to the expected value of the distance between any two nodes in the community, that is:

$$APL_j = \frac{1}{n\cdot(n-1)} \cdot \sum_{i\neq j} d(v_m, v_n) \text{ Eq. (A.6)}$$

In this formula, n is the number of nodes in the community j. $d(v_m, v_n)$ refers to the shortest path length between nodes m and n. If there is no connection between nodes m and n, then $d(v_m, v_n) = 0$.

Assortativity. If nodes with a high degree tend to be connected with other nodes with high degrees, then the network is regarded as homogeneous (i.e., they possess assortativity); otherwise, the network is considered heterogeneous (i.e., they do not possess assortativity) (Newman, 2003),. By studying the assortativity of communities in the network, the emission transfer mode among sectors can be better understood. The assortativity coefficient of community j is defined as:

$$r_j = \frac{\frac{1}{|D_j|}\cdot\sum k_m k_n - \left[\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot(k_m+k_n)\right]^2}{\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot({k_m}^2+{k_n}^2) - \left[\frac{1}{|D_j|}\cdot\sum\frac{1}{2}\cdot(k_m+k_n)\right]^2} \text{ Eq. (A.7)}$$

In this formula, $|D_j|$ is the total number of edges in community j, and k_m, k_n are the degrees of sectors m and n in the community, respectively. If the assortativity coefficient $r > 0$, the community is a homogeneous sub-network; if $r < 0$, the community is a heterogeneous sub-network.

1) Level 1: sector-level network structure variables

Detailed descriptive studies of the sector-level network variables in the embodied carbon emissions network, including degree, strength, and betweenness, can be found in our previous work *Carbon Communities and Hotspots for Carbon Emissions Reduction in China* (Huang et al., 2019). Therefore, these three metrics, i.e., degree, strength, and betweenness, are briefly introduced in this appendix. In addition, a detailed introduction about the clustering coefficient and closeness is provided in this appendix.

Degree. The in-degree and out-degree of sector i are given by the formulas Eq. (A.8) and Eq. (A.9), respectively. They refer to the number of a sector's import and export partner sectors on embodied carbon emissions.

$Degree_i^{in} = \sum_{i \neq j, i, j \in \mathcal{V}(N)} I\left[q_{ji} > 0\right]$ Eq. (A.8)

$Degree_i^{out} = \sum_{i \neq j, i, j \in \mathcal{V}(N)} I\left[q_{ij} > 0\right]$ Eq. (A.9)

In these formulas, I is an indicator function, and its value equals 1 when the number of carbon emissions transferred between two sectors is larger than 0.

Strength. The in-strength and out-strength of sector i are given by the formulas Eq. (A.10) and Eq. (A.11). They refer to the quantity of embodied emissions a sector imports from others and the quantity a sector exports to others.

$Strength_i^{in} = \sum_{i \neq j, i, j \in \mathcal{V}(N)} q_{ji}$ Eq. (A.10)

$Strength_i^{out} = \sum_{i \neq j, i, j \in \mathcal{V}(N)} q_{ij}$ Eq. (A.11)

Betweenness. The betweenness of sector i is given by the formula Eq. (A.13)

$Betweenness_i = fTJ_iTy$ Eq. (A.13)

In this formula, the row vector f is the carbon emission intensity of each sector, $T = LA$ (where L is the Leontief inverse matrix, and A is the direct technical coefficient matrix), J_i is an identity matrix. Column vector y represents the final demand for each sector's products. It calculates the number of emissions passing a sector in the embodied carbon emissions network.

Clustering Coefficient. In social networks, one phenomenon is widespread: Two people who are both friends of a third person are likely to know each other. This characteristic is called clustering and is usually measured by a clustering coefficient. Clustering can also be explained as the interconnectedness within a group of nodes. In a carbon emissions network, the clustering coefficient measures the completeness of a sector's local network. The larger the clustering coefficient of a node is, the more likely that its transfer paths form a small-scale interconnected sub-network (Newman, 2003). The clustering coefficient ($CC_{\mathbb{G}(i)}$) of sector i is defined as

$CC_{\mathbb{G}(i)} = \frac{\#\left\{jk \mid k \neq j, j \in N_{\mathbb{G}(i)}, k \in N_{\mathbb{G}(i)}\right\}}{d_{\mathbb{G}(i)}(d_{\mathbb{G}(i)} - 1)/2}$ Eq. (A.12)

In this formula, N is equal to the number of nodes contained in the network and $d_{\mathbb{G}(i)}$ represents the sum of the in-degrees and out-degrees of sector i in the network.

Closeness. The closeness of a node measures its distance to other nodes based on the shortest path. In a carbon emission network, in reference to Liang's (2016) adjusted betweeness algorithm, this research defines two forms of closeness: closeness-up and closeness-down. Closeness-up measures the total weights of the carbon emission transfer paths ending in a sector, and closeness-down measures the total weights of the carbon emission transfer paths starting in a sector. In other words, the two metrics measure the relative positions of a specific sector along a carbon emissions transfer path. Closeness-up measures a sector's importance as a consumer of carbon emissions, while closeness-down measures its importance as a producer. The closeness-up and closeness-down of sector i are defined in formulas Eq. (A.14) and Eq. (A.15), respectively:

$ClosenessUp_i = f \cdot (\sum_l^{\infty} A^l) \cdot J_i \cdot \mathbb{Y} = fTJ_i\mathbb{Y}$ Eq. (A.14)

$ClosenessDown_i = f \cdot J_i \cdot (\sum_l^{\infty} A^l) \cdot \mathbb{Y} = fJ_iT\mathbb{Y}$ Eq. (A.15)

Because the values of betweenness, closeness-up, and closeness-down are skewed and measured in kilotons, this research conducts a logarithmic transformation on the three variables to increase the model's reliability.

Appendix A.2. Communities of sectors in the carbon emissions network from 2007 to 2012

Com. ID	Community Name	Number of Sectors	Number of Provinces	Total Flows [1] (Unit: Thousand Tons)	Inflows [2] (Unit: Thousand Tons)	Percent of inflows from total flows (Unit: Thousand Tons)	Note
2007_1	Shanxi community 2007	30	1	306,989.32	159,314.40	51.90%	30 sectors of Shanxi
2007_2	Beijing-Tianjin-Hebei community 2007	89	3	665,177.64	394,872.31	59.36%	30 sectors of Beijing, 29 sectors of Tianjin, and 30 sectors of Hebei
2007_3	Inner Mongolia-Liaoning-Jilin-Heilongjiang community 2007	120	4	942,090.04	696,665.95	73.95%	30 sectors of Inner Mongolia, 30 sectors of Liaoning, 30 sectors of Jilin, and 30 sectors of Heilongjiang
2007_4	Zhejiang community 2007	29	1	299,809.90	237,799.47	79.32%	29 sectors of Zhejiang
2007_5	Anhui-Jiangsu-Shaanxi community 2007	60	3	612,819.87	457,543.56	74.66%	29 sectors of Anhui, 30 sectors of Jiangsu, and the petroleum and gas sector of Shaanxi
2007_6	Fujian community 2007	29	1	137,916.59	125,136.16	90.73%	29 sectors of Fujian
2007_7	Shandong	30	1	615,869.61	486,838.69	79.05%	30 sectors of Shandong
2007_8	Shanghai	27	1	154,645.35	136,276.6[illegible]	88.12%	27 sectors of Shanghai
2007_9	Hubei	30	1	213,210.84	164,67[illegible].68	77.23%	30 sectors of Hubei
2007_10	Hunan community 2007	29	1	193,091.16	156,723.06	81.17%	29 sectors of Hunan
2007_11	Guangdong-Guangxi-Guizhou-Yunnan community 2007	116	4	740,[illegible]0.4[illegible]	615,025.08	83.11%	29 sectors of Guangdong, 29 sectors of Guangxi, 29 sectors of Guizhou, and 29 sectors of Yunnan
2007_12	Hainan community 2007	28	1	18,294.25	16,456.02	89.95%	28 sectors of Hainan
2007_13	Chongqing-Sichuan community 2007	60	2	259,48[illegible].01	231,481.18	89.21%	30 sectors of Chongqing and 30 sectors of Sichuan
2007_14	Jiangxi community 2007	29	1	109,094.95	95,176.18	87.24%	29 sectors of Jiangxi
2007_15	Henan-Shaanxi community 2007	59	2	497,863.78	269,565.19	54.14%	30 sectors of Henan and 29 sectors of Shaanxi
2007_16	Gansu-Qinghai-Ningxia community 2007	86	3	150,999.44	108,195.74	71.65%	28 sectors of Gansu, 28 sectors of Qinghai, and 30 sectors of Ningxia
2007_17	Xinjiang-Gansu community 2007	32	2	102,364.38	77,962.76	76.16%	30 sectors of Xinjiang and 2 sectors of Gansu, i.e., petroleum and gas sector and refining and coking sector of Gansu
2010_1	Beijing-Tianjin-Hebei-Shanxi community 2010	91	3	832,340.85	519,403.85	62.40%	30 sectors of Beijing, 30 sectors of Tianjin, 30 sectors of Hebei, and the coal mining sector of Shanxi
2010_2	Shanxi community 2010	29	1	338,565.38	186,731.18	55.15%	29 sectors of Shanxi
2010_3	Inner Mongolia-Liaoning-Jilin-Heilongjiang community 2010	120	4	1,184,311.14	930,746.93	78.59%	30 sectors of Inner Mongolia, 30 sectors of Liaoning, 30 sectors of Jilin, and 30 sectors of Heilongjiang
2010_4	Shanghai community 2010	27	1	161,330.24	151,492.69	93.90%	27 sectors of Shanghai
2010_5	Zhejiang community 2010	29	1	315,033.89	252,608.21	80.18%	29 sectors of Zhejiang
2010_6	Anhui-Jiangsu community 2010	59	2	759,936.60	607,230.70	79.91%	29 sectors of Anhui and 30 sectors of Jiangsu
2010_7	Fujian community 2010	29	1	180,309.68	162,891.25	90.34%	29 sectors of Fujian
2010_8	Jiangxi community 2010	29	1	123,940.37	91,710.02	74.00%	29 sectors of Jiangxi
2010_9	Shandong	30	1	668,032.75	563,857.41	84.41%	30 sectors of Shandong
2010_10	Hubei community 2010	30	1	280,006.47	225,546.26	80.55%	30 sectors of Hubei
2010_11	Hunan community 2010	29	1	224,343.03	191,382.95	85.31%	29 sectors of Hunan
2010_12	Hainan community 2010	28	1	24,136.55	22,571.90	93.52%	28 sectors of Hainan
2010_13	Chongqing-Sichuan community 2010	60	2	382,756.71	336,965.16	88.04%	30 sectors of Chongqing and 30 sectors of Sichuan
2010_14	Guangdong-Guangxi-Guizhou-Yunnan community 2010	116	4	914,679.27	793,350.52	86.74%	29 sectors of Guangdong, 29 sectors of Guangxi, 29 sectors of Guizhou, and 29 sectors of Yunnan

Com. ID	Community Name	Number of Sectors	Number of Provinces	Total Flows [1] (Unit: Thousand Tons)	Inflows [2] (Unit: Thousand Tons)	Percent of inflows from total flows (Unit: Thousand Tons)	Note
2010_15	Shaanxi community 2010	30	1	183,457.65	128,053.72	69.80%	30 sectors of Shaanxi
2010_16	Gansu-Qinghai-Ningxia community 2010	88	3	207,074.85	153,537.48	74.15%	30 sectors of Gansu, 28 sectors of Qinghai, and 30 sectors of Ningxia
2010_17	Henan-Xinjiang community 2010	60	2	596,600.33	411,816.05	69.03%	30 sectors of Henan and 30 sectors of Xinjiang
2012_1	Hebei-Beijing community 2012	37	2	758,969.89	467,686.11	61.62%	30 sectors of Hebei and 7 sectors of Beijing
2012_2	Shanxi-Beijing community 2012	31	2	483,149.25	244,003.97	50.50%	30 sectors of Shanxi and the coal mining sector of Beijing
2012_3	Tianjin-Beijing-Inner Mongolia community 2012	77	3	864,690.17	486,298.42	56.24%	30 sectors of Tianjin, 29 sectors of Inner Mongolia, and 18 sectors of Beijing
2012_4	Liaoning-Jilin-Heilongjiang-Beijing community 2012	91	4	933,198.85	769,078.09	8[illegible].41%	30 sectors of Liaoning, 30 sectors of Jilin, and 30 sectors of Heilongjiang, and the wood processing and furnishing sector of Beijing
2012_5	Shanghai-Zhejiang community 2012	56	2	559,836.97	475,801.77	[illegible]4.9[illegible]%	27 sectors of Shanghai and 29 sectors of Zhejiang
2012_6	Jiangsu-Anhui-Beijing-Ningxia community 2012	61	4	1,034,650.91	828,555.[illegible]	80.08%	30 sectors of Jiangsu, 29 sectors of Anhui, the coal mining sector of Ningxia, and the metallurgy sector of Beijing
2012_7	Fujian community 2012	29	1	220,926.38	199,660.[illegible]0	90.37%	29 sectors of Fujian
2012_8	Jiangxi community 2012	29	1	158,945.48	12[illegible],113.88	76.20%	29 sectors of Jiangxi
2012_9	Shandong-Beijing-Inner Mongolia community 2012	33	3	84[illegible],017.8[illegible]	791,041.29	93.61%	30 sectors of Shandong, the metal mining sector of Beijing, the petroleum and gas sector of Beijing, and the petroleum and gas sector of Inner Mongolia
2012_10	Henan community 2012	30	1	511,0[illegible].76	323,262.31	63.25%	30 sectors of Henan
2012_11	Hubei community 2012	30	1	373,377.40	366,084.97	98.05%	30 sectors of Hubei
2012_12	Hunan community 2012	29	1	2[illegible]2,280.80	214,643.94	78.83%	29 sectors of Hunan
2012_13	Guangdong community 2012	29	1	459,988.24	418,628.72	91.01%	29 sectors of Guangdong
2012_14	Guangxi-Hainan community 2012	58	2	226,869.60	181,912.54	80.18%	29 sectors of Guangxi and 29 sectors of Hainan
2012_15	Sichuan community 2012	30	[illegible]	310,668.62	296,215.88	95.35%	30 sectors of Sichuan
2012_16	Chongqing-Guizhou-Yunnan community 2012	88	3	585,524.86	436,197.93	74.50%	30 sectors of Chongqing, 29 sectors of Guizhou and 29 sectors of Yunnan
2012_17	Qinghai community 2012	30	1	41,777.12	36,804.02	88.10%	30 sectors of Qinghai
2012_18	Shaanxi-Gansu-Ningxia community 2012	[illegible]	3	537,411.07	334,010.55	62.15%	30 sectors of Shaanxi, 30 sectors of Gansu, and 29 sectors of Ningxia
2012_19	Xinjiang community 2012	30	1	250,476.59	186,889.57	74.61%	30 sectors of Xinjiang

Table A.1. Communities of sectors in the carbon emissions network from 2007 to 2012

Note: (1) The embodied carbon emissions network in reduced form is used in these calculations. (2) Table heading explanation. [1] Total flow: The amount of embodied carbon emissions the sectors of a community import and export. [2] Inflows: The amount of embodied carbon emissions transmitted amid a community.

Appendix A.3. Random effect of the sector-level transmission variables in communities

Com. ID	Relative Out-Degree	Relative Out-Strength	Clustering	Closeness_up	Closeness_down	Betweenness
2007_1	0.0374	3.1272	-0.0505	0.4248	1.0206	-0.4240
2007_2	-0.0375	0.0434	-0.0719	0.1078	0.9798	-0.1800
2007_3	0.0370	0.0241	-0.0610	0.1495	0.9638	-0.1680
2007_4	0.0952	-0.0557	-0.0628	0.2527	1.0157	-0.3047
2007_5	0.1085	0.1398	-0.0617	0.2873	1.0269	-0.3392
2007_6	0.0325	1.9277	-0.0619	0.3256	1.0552	-0.3738
2007_7	0.0632	1.8684	-0.0457	0.2844	0.9585	-0.2321
2007_8	0.0485	0.2981	-0.0692	0.2404	1.0435	-0.3232
2007_9	0.0100	1.8456	-0.0610	0.2935	1.0219	-0.3310
2007_10	0.0788	0.0336	-0.0593	0.2059	0.9847	-0.2264
2007_11	0.1067	0.0645	-0.0581	0.2158	1.0089	-0.2295
2007_12	0.0656	5.3869	-0.0534	0.6274	1.1898	-0.6662
2007_13	0.0303	0.2902	-0.0694	0.2043	1.0328	-0.2801
2007_14	0.0464	2.5288	-0.0542	0.3582	1.0394	-0.3649
2007_15	0.1500	0.0445	-0.0563	0.3228	1.0133	-0.3526
2007_16	0.2621	0.9365	-0.0214	0.3111	0.9181	-0.1289
2007_17	0.0916	0.3824	-0.0423	0.1280	0.9006	-0.0302
2010_1	0.0170	3.2727	-0.0553	0.3925	1.0577	-0.4081
2010_2	-0.0033	3.5971	-0.0547	0.4212	1.0426	-0.4399
2010_3	0.0645	3.3368	-0.0445	0.4175	1.0192	-0.3768
2010_4	-0.0085	1.[illegible]346	-0.0717	0.2694	1.0619	-0.3656
2010_5	-0.0092	1.5244	-0.0653	0.2443	1.0270	-0.2974
2010_6	0.0047	1.9907	-0.0623	0.2991	1.0365	-0.3440
2010_7	0.0130	1.8264	-0.0672	0.3162	1.0725	-0.3932
2010_8	0.0791	2.2124	-0.0482	0.3471	1.0081	-0.3199
2010_9	0.0414	1.7176	-0.0504	0.2742	0.9643	-0.2483
2010_10	0.0297	1.8058	-0.0578	0.2940	1.0161	-0.3135
2010_11	0.0360	2.1407	-0.0552	0.3239	1.0170	-0.3329
2010_12	0.1335	1.0375	-0.0437	0.1921	0.9961	-0.1070
2010_13	0.0826	0.1696	-0.0658	0.2583	1.0410	-0.3260
2010_14	0.0515	2.5321	-0.0573	0.3892	1.0644	-0.4208
2010_15	0.0316	2.3589	-0.0545	0.3256	1.0212	-0.3289
2010_16	0.1857	0.3966	-0.0320	0.1538	0.9226	0.0012
2010_17	0.0314	2.9528	-0.0510	0.3840	1.0167	-0.3772
2012_1	-0.0044	2.4838	-0.0556	0.3100	0.9994	-0.3169
2012_2	0.0594	0.0747	-0.0662	0.2509	1.0110	-0.3225
2012_3	0.0371	3.2849	-0.0500	0.3850	1.0400	-0.3684
2012_4	0.0262	0.5023	-0.0653	0.2409	0.9961	-0.3028
2012_5	-0.0307	1.1330	-0.0741	0.2289	1.0526	-0.3316
2012_6	-0.0456	1.6225	-0.0701	0.2509	1.0280	-0.3335
2012_7	-0.0019	2.4490	-0.0669	0.3623	1.0835	-0.4440
2012_8	0.0192	1.2762	-0.0606	0.2333	1.0058	-0.2583
2012_9	0.0209	0.5297	-0.0590	0.1791	0.9542	-0.1900
2012_10	0.0330	1.4259	-0.0554	0.2581	0.9808	-0.2590
2012_11	-0.0156	2.2418	-0.0620	0.2832	1.0318	-0.3208

Com. ID	Relative Out-Degree	Relative Out-Strength	Clustering	Closeness_up	Closeness_down	Betweenness
2012_12	-0.0266	2.6513	-0.0660	0.3447	1.0651	-0.4167
2012_13	0.0572	0.2636	-0.0687	0.2586	1.0415	-0.3431
2012_14	-0.0374	1.8055	-0.0758	0.2649	1.0983	-0.3784
2012_15	-0.0236	1.3906	-0.0694	0.2304	1.0389	-0.3044
2012_16	-0.0467	2.5339	-0.0690	0.3016	1.0705	-0.3810
2012_17	0.1952	-0.2075	-0.0197	0.1226	0.7898	0.0996
2012_18	0.0982	0.7656	-0.0568	0.2725	1.0225	-0.2872
2012_19	0.0862	2.9550	-0.0431	0.4276	1.0026	-0.3851

Table A.2 Random effect of the sector-level transmission variables in communities

Appendix A.4 Robustness check - Relationship between the embodied carbon emissions network structure and sectors' direct carbon emissions (one-year lag)

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Fixed effect				
Community level characteristics				
Size		0.0228	-0.0165	-0.0219
		(0.0187)	(0.0121)	(0.0132)
Density		0.0077	-0.0087	-0.0196
		(0.0176)	(0.0122)	(0.0135)
Average path length		0.0035	-0.0134**	-0.0176***
		(0.0070)	(0.0057)	(0.0059)
Assortativity		0.0093	-0.0122	-0.0149
		(0.0107)	(0.0[illegible]82)	(0.0089)
Individual characteristics				
Relative Out-degree	0.0133	0.0124	-0.020[illegible]	0.0799***
	(0.0084)	(0.0084)	(0.[illegible]368)	(0.0182)
Relative Out-strength	0.0257***	0.0264***	1.2[illegible]01***	0.3929***
	(0.0074)	(0.0075)	(0.[illegible]226)	(0.0706)
Clustering Coefficient	-0.0844***	-0.0846***	-0.0793***	-0.0631***
	(0.0048)	(0.00[illegible]8)	(0.0055)	(0.0053)
Closeness-up	0.1950***	0.19[illegible]3***	0.3599***	0.2645***
	(0.0074)	(0.0074)	(0.0217)	(0.0207)
Closeness-down	0.9806***	0.9808***	0.9909***	0.9755***
	(0.0080)	(0.0080)	(0.0143)	(0.0151)
Betweenness	-0.1369***	-0.1385***	-0.2260***	-0.2507***
	(0.0103)	(0.0103)	(0.0226)	(0.0237)
Sector economic characteristics				
Compensation of employees				0.0958***
				(0.0138)
Net taxes on production				0.0062
				(0.0045)
Depreciation of fixed capital				-0.0443***
				(0.0103)
Operating surplus				0.0103**
				(0.0043)
Intermediate input/ final output ratio				0.0064
				(0.0050)
Coal/total fossil fuel ratio				-0.0095***
				(0.0035)
GDP				0.0515***
				(0.0163)
Time				
Year 2010	-0.0213	-0.0214	0.0244*	-0.0330**
	(0.0170)	(0.0176)	(0.0129)	(0.0143)
Year 2012	-0.0664***	-0.0636***	-0.0318**	-0.0890***
	(0.0166)	(0.0172)	(0.0130)	(0.0148)
Sector				
Manufacturing sector	0.0137	0.0152	0.0487***	0.0812***
	(0.0117)	(0.0121)	(0.0122)	(0.0144)
Service sector	0.0822***	0.0835***	0.0896***	0.0757***
	(0.0146)	(0.0149)	(0.0142)	(0.0163)
Random effects (variance)				
Relative Out-degree			0.0447***	0.0059**
			(37.155)	(16.785)
Relative Out-strength			1.3067***	0.0893***
			(63.601)	(23.075)
Clustering Coefficient			0.0004*	0.0004**
			(15.407)	(16.513)

	Dependent variable: total carbon emissions (logarithmic)			
	(1)	**(2)**	**(3)**	**(4)**
Closeness-up			0.0188*** (231.712)	0.0161*** (158.999)
Closeness-down			0.0080*** (107.565)	0.0093*** (128.337)
Betweenness			0.0203*** (260.772)	0.0230*** (322.534)
Model fitting information				
intra-class correlation (ICC)	0.040	0.043	0.980	0.846
AIC	-685.22	-650.36	-1311.75	-1455.43
BIC	-614.62	-556.23	-1058.76	-1161.26
Observed sample size	2,653	2,653	2,653	2,653

Table A.3. Relationship between the embodied carbon emissions network structure and sectors' direct carbon emissions (one-year lag)

Note: ***, **, and * indicate that the data are significant at 1%, 5%, and 10% levels, respectively, and the standard errors of the estimated coefficients are in parentheses.
For random effect (variance), the values in brackets are the likelihood ratio test statistics results.
Closeness-up, closeness-down, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus, and GDP are logarithmically transformed.

Appendix A.5 Robustness check - Relationship between the embodied carbon emissions network structure and sectors' direct carbon emissions (regression in a yearly manner)

	Dependent variable: total carbon emissions (logarithmic)		
	2007	**2010**	**2012**
Fixed effect			
Community level characteristics			
Size	-0.0353* (0.0157)	-0.0226* (0.0121)	-0.0256 (0.0302)
Density	-0.0324* (0.0178)	-0.0151 (0.0125)	-0.0306 (0.0226)
Average path length	-0.0054 (0.0060)	0.0172 (0.0102)	-0.0038 (0.0089)
Assortativity	-0.0297** (0.0137)	-0.0143 (0.0115)	-0.0028 (0.0110)
Individual characteristics			
Relative Out-degree	0.1414** (0.0450)	-0.0814 (0.0482)	-0.0544 (0.0393)
Relative Out-strength	0.0346*** (0.0083)	3.0401*** (0.6280)	1.8925*** (0.3972)
Clustering Coefficient	-0.0532*** (0.0091)	-0.0564*** (0.0060)	-0.0651*** (0.0069)
Upward closeness	0.2537*** (0.0425)	0.3748*** (0.0172)	0.2782*** (0.0202)
Downward closeness	0.9935*** (0.0208)	1.0432*** (0.0097)	1.0243*** (0.0218)
Betweenness	-0.2636*** (0.0429)	-0.2315*** (0.0253)	-0.3214*** (0.0353)
Sector economic characteristics			
Compensation of employees	0.1664*** (0.0241)	0.0695*** (0.0151)	0.0929*** (0.0160)
Net taxes on production	0.0145** (0.0070)	-0.0073 (0.0065)	0.0026 (0.0058)
Depreciation of fixed capital	-0.0636*** (0.0162)	-0.0565*** (0.0116)	-0.0681*** (0.0133)
Operating surplus	0.0169**	-0.0028*	0.0112**

	Dependent variable: total carbon emissions (logarithmic)		
	2007	**2010**	**2012**
	(0.0080)	(0.0053)	(0.0046)
Intermediate input/ final output ratio	0.0239***	-0.0132**	0.0140**
	(0.0082)	(0.0059)	(0.0063)
Coal/total fossil fuel ratio	0.0007	-0.0047	-0.0013
	(0.0060)	(0.0038)	(0.0042)
GDP	0.0238	-0.0038	0.0847***
	(0.0264)	(0.0198)	(0.0209)
Sector			
Manufacturing sector	0.0593***	0.1675***	0.1071***
	(0.0124)	(0.0392)	(0.0214)
Service sector	0.0265	0.1206***	0.0638
	(0.0185)	(0.0379)	(0.0234)
Random effects (variance)			
Relative Out-degree	0.0258***	0.0216[illegible]	0.0167
	(29.276)	(19.[illegible]26)	(6.278)
Relative Out-strength	0.0003	148.[illegible]	2.3138***
	(0.906)	(70.8[illegible]3)	(44.198)
Clustering Coefficient	0.0003	0.0001	0.0004
	(4.908)	(4.735)	(10.426)
Closeness-up	0.0255***	0.0130***	0.0050***
	(75.651)	(50.401)	(22.318)
Closeness-down	0.0044***	0.0010	0.0071***
	(25.67[illegible])	(9.813)	(83.440)
Betweenness	0.02[illegible]5[illegible]	0.0105***	0.0178***
	(123.7[illegible]4)	(105.107)	(148.206)
Model fitting information			
intra-class correlation (ICC)	[illegible].753	0.999	0.995
AIC	-377.38	-1218.13	-1013.75
BIC	-147.78	-988.47	-783.99
Observed sample size	883	884	886

Table A.4. Relationship between the embodied carbon emissions network structure and sectors' direct carbon emissions (2007, 2010,2012)

Note: ***, **, and * indicate that the data are significant at 1%, 5%, and 10% levels, respectively, and the standard errors of the estimated coefficients are in parentheses.

For random effect (variance), the values in brackets are the likelihood ratio test statistics results.

Upward closeness, downward closeness, betweenness, compensation of employees, net taxes on production, depreciation of fixed capital, operating surplus, and GDP are logarithmically transformed.

References

Bassett, D.S., Wymbs, N.F., Porter, M.A., Mucha, P.J., Carlson, J.M., Grafton, S.T., 2011. Dynamic reconfiguration of human brain networks during learning. Proc. Natl. Acad. Sci. 108, 7641–7646.
Bliese, P.D., Halverson, R.R., Schriesheim, C.A., 2002. Benchmarking multilevel methods in leadership. The articles, the model, and the data set. Leadersh. Q. 13, 3–14. doi:10.1016/S1048-9843(01)00101-1
Blondel, V.D., Guillaume, J.-L., Lambiotte, R., Lefebvre, E., 2008. Fast unfolding of communities in large networks. J. Stat. Mech. theory Exp. 2008, P10008.
Bowers, A.J., Urick, A., 2011. Does high school facility quality affect student achievement? A two-level hierarchical linear model. J. Educ. Finance. 72–94.
Chen, D., Chen, S., Jin, H., 2018. Industrial agglomeration and CO2 emissions: Evidence from 187 Chinese prefecture-level cities over 2005–2013. J. Clean. Prod. 172, 993–1003. doi:10.1016/j.jclepro.2017.10.068
Clauset, A., Newman, M.E.J., Moore, C., 2004. Finding community structure in very large networks. Phys. Rev. E 70, 066111.
Cohen, G., Jalles, J.T., Loungani, P., Marto, R., Wang, G., 2019. Decoupling of Emissions and GDP: Evidence from Aggregate and Provincial Chinese Data. Energy Econ. 77, 105–118. doi:10.1016/j.eneco.2018.03.030
Del Río-Chanona, R.M., Grujić, J., Jensen, H.J., 2017. Trends of the world input and output network of global trade. PLoS One 12, 1–15. doi:10.1371/journal.pone.0170817
Duan, C., Chen, B., Feng, K., Liu, Z., Hayat, T., Alsaedi, A., Ahmad, B., 2018. Interregional carbon flows of China. Appl. Energy 227, 342–352. doi:10.1016/j.apenergy.2018.01.028
Duan, H., Mo, J., Fan, Y., Wang, S., 2018. Achieving China's energy and climate policy targets in 2030 under multiple uncertainties. Energy Econ. 70, 45–60. doi:10.1016/j.eneco.2017.12.022
Gentry, W.A., Martineau, J.W., 2010. Hierarchical linear modeling as an example for measuring change over time in a leadership development evaluation context. Leadersh. Q. 21, 645–656.
Hanaka, T., Kagawa, S., Ono, H., Kanemoto, K., 2017. Finding environmentally critical transmission sectors, transactions, and paths in global supply chain networks. Energy Econ. 68, 44–52. doi:10.1016/j.eneco.2017.09.012
Huang, L., Kelly, S., Lu, X., Lv, K., Shi, X., Ciurco, D., 2019. Carbon Communities and Hotspots for Carbon Emissions Reduction in China. Sustainability 11, 5508. doi:10.3390/su11195508
Hubert, L., Arabie, P., 1985. Comparing partitions. J. Classif. Vol. 193–218.
Jia, J., Li, H., Zhou, J., Jiang, M., Dong, D., 2018. Analysis of the transmission characteristics of China's carbon market transaction price volatility from the perspective of a complex network. Environ. Sci. Pollut. Res. 25, 7369–7381.
Jiang, M., Gao, X., Guan, Q., Hao, X., An, F., 2019. The structural roles of sectors and their contributions to global carbon emissions: A complex network perspective. J. Clean. Prod. 208, 426–435. doi:10.1016/j.jclepro.2018.10.127
Kagawa, S., Suh, S., Hubacek, K., Wiedmann, T., Nansai, K., Minx, J., 2015. CO2emission clusters within global supply chain networks: Implications for climate change mitigation. Glob. Environ. Chang. 35, 486–496. doi:10.1016/j.gloenvcha.2015.04.003
Kanemoto, K., Hanaka, T., Kagawa, S., Nansai, K., 2018. Industrial clusters with substantial carbon-reduction potential. Econ. Syst. Res. doi:10.1080/09535314.2018.1492369
Klein, K.J., Kozlowski, S.W.J., 2000. Multilevel theory, research, and methods in organizations: Foundations, extensions and new directions. Jossey-Bass, San Francisco.
Leeuw, D., Jan, E.M., Harvey, G., 2008. Handbook of multilevel analysis. Springer, New York, USA
Lenzen, M., Moran, D., Kanemoto, K., Foran, B., Lobefaro, L., Geschke, A., 2012. International trade drives biodiversity threats in developing nations. Nature 486, 109–112. doi:10.1038/nature11145
Leontief, W., 1970. Environmental Repercussions and the Economic Structure : An Input-Output Approach. Rev. Econ. Stat. 52, 262–271.
Li, Z., Sun, L., Geng, Y., Dong, H., Ren, J., Liu, Z., Tian, X., Yabar, H., Higano, Y., 2017. Examining industrial structure changes and corresponding carbon emission reduction effect by combining input-output analysis and social network analysis: A comparison study of China and Japan. J. Clean. Prod. 162, 61–70. doi:10.1016/j.jclepro.2017.05.200

Liang, S., Feng, Y., Xu, M., 2015. Structure of the Global Virtual Carbon Network: Revealing Important Sectors and Communities for Emission Reduction. J. Ind. Ecol. 19, 307–320. doi:10.1111/jiec.12242

Liang, S., Qu, S., Xu, M., 2016. Betweenness-Based Method to Identify Critical Transmission Sectors for Supply Chain Environmental Pressure Mitigation. Environ. Sci. Technol. 50, 1330–1337. doi:10.1021/acs.est.5b04855

Luke, D.A., 2004. Multilevel Modeling. SAGE, St. Louis, USA.

Martin, S., Brown, W.M., Klavans, R., Boyack, K.W., 2011. OpenOrd : An Open-Source Toolbox for Large Graph Layout, in: Visualization and Data Analysis 2011, Proceeding of Society of Photo-Optical Instrumentation Engineers. p. Vol. 7868, 786806.

Meilă, M., 2003. Comparing Clusterings by the Variation of Information, in: Schölkopf B., W.M.K. (Ed.), Learning Theory and Kernel Machines. Springer, Berlin, Heidelberg.

Mo, J., Schleich, J., Fan, Y., 2018. Getting ready for future carbon abatement under uncertainty – Key factors driving investment with policy implications. Energy Econ. 70, 453–464. doi:10.1016/j.eneco.2018.01.026

Newman, M.E., 2003. Mixing patterns in networks. Phys. Rev. 67, 20126.

Otani, K., Kim, B.J., Waterman, B., 2012. Patient satisfaction and organizational impact: a hierarchical linear modeling approach. Health Mark. Q. 29, 250–269.

Raudenbush, W.S., Bryk, A.S., 2002. Hierarchical linear models: Applications and data analysis methods. Sage. Thousand Oaks, USA.

Serrano, M.Á., Boguñá, M., Vespignani, A., 2009. Extracting the multiscale backbone of complex weighted networks. Proc. Natl. Acad. Sci. U. S. A. 106, 6483–6488.

Wang, Y., Wang, J., 2019. Does industrial agglomeration facilitate environmental performance: New evidence from urban China? J. Environ. Manage. 248, 109244. doi:10.1016/j.jenvman.2019.07.015

Wang, Z., Xiao, C., Niu, B., Deng, L., Liu, Y., 2017. Identify sectors' role on the embedded CO2 transfer networks through China's regional trade. Ecol. Indic. 80, 114–123. doi:10.1016/j.ecolind.2017.05.013

Wiedmann, T.O., Schandl, H., Lenzen, M., Moran, D., Suh, S., West, J., Kanemoto, K., 2015. The material footprint of nations. Proc. Natl. Acad. Sci. 112, 6271–6276. doi:10.1073/pnas.1220362110

Wu, J., Wu, Y., Cheong, T.S., 2021. New evidence on the convergence and regional clusters in China: a weighted continuous distribution dynamics approach. Appl. Econ. 53, 976–995.

Xu, X., Huo, H., Liu, J., Shan, Y., Li, Y., Zheng, H., Guan, D., Ouyang, Z., 2018. Patterns of CO2emissions in 18 central Chinese cities from 2000 to 2014. J. Clean. Prod. 172, 529–540. doi:10.1016/j.jclepro.2017.10.136

Yang, H., Lu, Z., Shi, X., Mensah, I.A., Luo, Y., Chen, W., 2021. Multi-region and multi-sector comparisons and analysis of industrial carbon productivity in China. J. Clean. Prod. 279, 123623. doi:10.1016/j.jclepro.2020.123623

Zhao, Y., Cao, Y., Shi, X., Wang, S., Yang, H., Shi, L., Li, H., Zhang, J., 2021. Critical transmission paths and nodes of carbon emissions in electricity supply chain. Sci. Total Environ. 755, 142530. doi:10.1016/j.scitotenv.2020.142530

Zhang, Y.-J., Jin, Y.-L., Zhu, T.-T., 2018. The health effects of individual characteristics and environmental factors in China: Evidence from the hierarchical linear model. J. Clean. Prod. 194, 554–563.

Zheng, H., Fath, B.D., Zhang, Y., 2017. An Urban Metabolism and Carbon Footprint Analysis of the Jing–Jin–Ji Regional Agglomeration. J. Ind. Ecol. 21, 166–179. doi:10.1111/jiec.12432

Zhou, X., Zhang, M., Zhou, Meihua, Zhou, Min, 2017. A comparative study on decoupling relationship and influence factors between China's regional economic development and industrial energy-related carbon emissions. J. Clean. Prod. 142, 783–800. doi:10.1016/j.jclepro.2016.09.115

Highlights

- Interdisciplinary methods are used to detect and examine the carbon communities
- The carbon communities are detected data-driven with no pre-assumption
- The effects of communities on carbon emissions are examined to inform policy-making
- Provide direction for local governments' external collaboration for a synergy