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Analyzing the Differences in the Quantitative and Spatial Characteristics of Inter-Provincial Embodied Carbon Transfers in China Induced via Various Demand Factors

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Abstract: The development of human society has led to the growing consumption of industrial products, which generates significant amounts of carbon emissions. However, relatively few in-depth studies have been conducted on the influence of different demand factors (e.g., household consumption, government consumption, export, and capital formation) on carbon emissions, which hinders the development of targeted industrial policies. To address this issue, an analytical framework based on input–output theory, the hypothesis extraction method, and complex network analysis was established to estimate the intrinsic influence of different demand factors on the embodied carbon transfer between provinces in China. The key findings can be summed up as follows: (1) The macro direction of China's embodied carbon transfer runs from resource-rich northern provinces to industrially developed southern provinces. (2) From the perspective of different demand factors, capital formation is the most significant contributor to China's embodied carbon transfer, with the construction industry being the most important driver. In contrast, government consumption causes the least embodied carbon transfer, but it has the highest average carbon emission intensity. (3) According to complex network theory, the carbon transfer networks via provinces and industries caused by exports are the most concentrated, with the manufacture of electrical machinery and electronic equipment serving as the main source of demand. In contrast, the carbon transfer network resulting from household consumption exhibits a high level of decentralization, with dominant sectors including electric power, gas and water production, and supply and other services. Based on these findings, this study is expected to contribute targeted suggestions with which provinces and industries can formulate demand-side carbon reduction policies for different demand factors, which will contribute to the achievement of "carbon peaking and carbon neutrality".

Keywords: embodied carbon transfer; demand factors; hypothetical extraction method; complex network analysis

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1. Introduction

As a result of the advancement of industrial society and the affluence of people, the demand for goods and services is constantly increasing, leading to record-breaking carbon emissions released due to modern industry, which causes serious climate change problems [1–3]. As climate warming threatens the survival of humanity, numerous countries have initiated shifts in their conventional patterns of industrial development to promote the reduction of carbon emissions [4–6]. As one of the most important developing countries and carbon emitters (since 2006), China has actively participated in carbon reduction efforts [7,8]. In 2020, the reduction in China's average carbon intensity met the promised target, falling by 48.4% from 2005 [9]. As part of its efforts to curb warming, the Chinese government has made international commitments to achieve carbon peaking and carbon neutrality by 2030 and 2060, respectively [10,11].

However, with the implementation of the "dual circulation" strategy, encompassing both domestic and foreign markets, the integration process of regional economics is accelerating, and inter-provincial economic connections are progressively intensifying [12]. In this case, industrial production and final consumption may take place in provinces with completely different technological levels, resource endowments, industrial structures, and social environments [13]. This indicates that the transfer of goods and services induced via trade constitutes a complex network that links provinces and sectors [14]. If the government focuses on specific industries or provinces and ignores the impact of trade networks in its decision-making, the effectiveness of carbon mitigation policies may be weakened, and the low-carbon transformation of the economy may be hindered. Therefore, in order to minimize carbon emissions, it is essential to understand the specific linkages and transfer features of carbon emissions across the provinces and sectors in China to assist in making targeted carbon mitigation decisions.

With the development of domestic inter-regional trade, carbon emissions circulating in commodity flows are also increasing [15]. The final demand, which includes exports, household consumption, government consumption, and capital formation, serves as a pull factor for the consumption and circulation of total social goods, and it drives the continuous transfer of embodied carbon emissions (ECEs) [16–18]. However, different factors on the demand side have significant and differential effects on the transfer of ECEs and their spatial characteristics between sectors at the inter-provincial level [19,20], and there are relatively few studies that have systematically analyzed the characteristics of ECEs caused by different demand factors [21–23]. This will impede the development of industrial carbon reduction policies that address different demand factors. Therefore, it is imperative to comprehensively investigate the disparities in the effects of various demand factors on the inter-provincial transfer of ECEs and their spatial characteristics.

Furthermore, the thriving commodity trade drives the transfer of ECEs across provinces and sectors [24]. The multi-directional flow of carbon emissions constitutes a complex network, making it challenging to evaluate the interaction effect of specific sectors with others in terms of carbon emissions [25]. However, most existing studies have considered final demand an indivisible whole and studied its influence on the inter-provincial transfer network of ECEs while ignoring the disparities of different demand factors in this network [26,27]. This does not facilitate the provision of targeted, scientific, and rational decision support for carbon reduction. Therefore, complex network analysis (CNA) was adopted to assess the spatial characteristics of inter-sectoral ECE transfer networks with different demand factors by computing network parameters.

In summary, a comparative analysis of the characteristics of ECEs and their transfer networks resulting from different demand factors in China is crucial for the development of scientific and targeted demand-side strategies for carbon mitigation. The rest of the study is structured as follows: Section 2 presents the relevant literature. Section 3 describes the methodology and data sources. Section 4 discusses the findings of the study. Section 5 presents policy suggestions. Section 6 draws conclusions.

2. Literature Review and Contributions

2.1. Literature Review

Since inter-provincial trade driven by final demand constitutes a significant ECE, the study of demand factors can identify the transfer characteristics and key sectors of ECEs and allow for theoretical suggestions for the development of demand-side emission reduction policies [28–32]. In most existing studies, final demand has been considered an indivisible whole to analyze its driving effects on carbon emissions and transfers [33–38]. For instance, Xu et al. [35] analyzed the final demand-driven CO_2 embodied in goods and services and revealed its provincial distribution characteristics. Additionally, there are studies that have focused on individual factors of final demand, such as household consumption [39,40], capital formation [41,42], and exports [43]. Yu et al. [40] comparatively analyzed the carbon footprint associated with household consumption and its driver factors in China and Japan and investigated the effects of consumption expenditure and technology on them. Hata et al. [42] calculated the materials and their embodied carbon emissions consumed by the industrial sector in Japan, driven by the capital formation factor, and they provided investment policy suggestions. From an export perspective, Tang et al. [43] examined the variation in China's export-side carbon emissions from 1997 to 2017 and explored the impact of substitution effects on the production structure.

In addition to a specific demand, the differential impacts of various demand factors on carbon emissions have been compared in several studies [17,44,45]. Xu et al. [17] delineated the final demand into six parts to assess the different impact of demand factors when calculating the embodied carbon emissions in Guangdong. Jiang et al. [45] accounted for carbon emissions due to different demand factors in two typical metropolitan cities, Beijing and Shanghai, and provided targeted policy recommendations. In terms of energy, Zhang et al. [44] investigated the driving effect of different demand factors on the energy consumption of Shanxi Province and located the key demands and sectors. The above studies mainly focused on analyzing the effect of various demand-side factors on ECEs, while relatively few studies have been conducted on the transfer pathways and spatial characteristics of ECEs. Furthermore, a systematic comparative analysis of the inter-provincial transfer of ECEs driven by various demand factors is still lacking. If the differences in ECEs driven by different demand factors are ignored by policymakers, their inherent characteristics may be misunderstood, preventing the development of demand-specific emission reduction policies. This could negatively affect carbon mitigation targets in key sectors and hinder the fulfillment of the dual-carbon strategy.

The analysis of inter-provincial carbon linkages is a crucial method of understanding carbon emissions in industrial economies. It involves assessing the ECEs in input–output (I–O) relationships between sectors and identifying key sectors and linkage pathways [46]. The classical multiplier method (CMM) proposed by Chenery and Watanabe [47] has been widely used in the study of environmental I–O systems [48–51]. However, it has been argued that CMM ignores the indirect impact of carbon emissions caused by inter-sectoral size disparities and that the intensity of inter-sectoral carbon transfers may be misestimated [22,52]. To address this issue, the hypothesis extraction method (HEM) has been developed as an alternative to CMM. It measures the direct and implied effects of a given sector by hypothetically eliminating that sector's linkages from the system and comparing the difference between the original and hypothetical systems. HEM provides a decomposition emission account of forward, backward, hybrid, and internal linkages that represent the carbon emissions caused by the self-consumption, repurchases, imports, and exports of the sector, respectively [53]. Therefore, HEM is more suitable than CMM for assessing the carbon transfer in a complex system with multiple sectors [54]. HEM has been used by some scholars to calculate inter-sectoral linkages such as carbon, water, and energy [55–58]. For example, Wen et al. [56] examined the impact of the COVID-19 epidemic on ECEs in China based on HEM and monthly economic data. Li et al. [55] constructed an energy consumption model based on HEM to quantitatively analyze the energy linkages of thirty Chinese provinces. Deng and Qin [58] utilized HEM to account for changes in the embodied water trade between the US and China from 2006 to 2016. Yuan et al. [57] estimated China's manufacturing carbon emissions for 2007–2017 based on HEM and further decomposed its driving factors. In general, compared with the traditional CMM, HEM can scientifically assess the direct and implied carbon relationships in a given sector and deeply investigate the characteristics of sector–system interactions. Therefore, HEM was employed in this study to calculate inter-provincial ECEs and to measure the comprehensive impacts of each sector on the overall carbon emissions of the system.

The directional transfer of ECEs between sectors induced via the commodity trade constitutes a vast and complex network. Assessing the spatial characteristics of this network and its impact on ECEs can contribute to the identification of key sectors and provinces and to planning targeted emission reduction policies, but this is challenging work [27]. Fortunately, CNA provides an effective approach to quantifying the system's intrinsic characteristics based on network indicators and identifying key node sectors [59]. By abstracting complex relationships into networks and nodes, CNA can offer theoretical references for policy formulation targeting industrial cluster networks. Currently, CNA has been broadly applied in the investigation of input–output-related networks [25,60–65]. For instance, Cheng et al. [62] studied the spatial characteristics of global land transfer networks based on agricultural land and trade data. Dimitrios. et al. [25] explored network indicators between the Greek electronic information sector and the system based on CNA. Zhao et al. [65] constructed a pollutant transfer network for the light industry in major economies around the world and revealed its structural characteristics and key transfer pathways. In order to deeply investigate the interaction between industrial networks and carbon emissions, CNA was introduced by some scholars to explore the spatial features of carbon transfer [1,26,45,66]. Wang et al. [66] utilized CNA to analyze the inter-sectoral linkages of ECEs in China and identified the key intermediary sectors. Jiang et al. [45] constructed a city-centered I–O network and examined the driving factors of Beijing and Shanghai's networks and their role in the global carbon network. Huo et al. [26] studied the evolution of ECE network features in the Chinese construction sector. However, discrepancies in the spatial characteristics of carbon transfer networks induced via different demand factors have been less studied based on CNA. This may result in important network characteristics and nodal sectors of different demand factors not being identified, leading to a misinterpretation of the role played by each demand factor. Therefore, a CNA of different final demands is necessary to understand the carbon interaction mechanisms and spatial characteristics of various demand factors.

2.2. Research Gap

Many studies have been dedicated to analyzing the ECEs induced by trade between different regions, which have obtained rich practical and theoretical achievements. However, there are still some research gaps. First, in most existing studies, final demand is considered an indivisible whole to analyze its driving effects on ECEs. Nevertheless, there is still a lack of systematic comparative studies on the effects of different demand factors on ECEs and their spatial characteristics. Second, many studies have utilized CMM in an I–O framework to measure carbon linkages between provinces, which has been criticized by some scholars as ignoring the indirect effects of sector size on carbon emissions, and they cannot accurately assess the intensity of carbon transfers. Third, CNA has rarely been used to systematically analyze the linkage strength and spatial characteristics of carbon transfer networks influenced by different demand factors from a demand-side perspective. Addressing these research gaps is essential for exploring the influence mechanisms of different demand factors on inter-provincial carbon transfer.

2.3. Objectives and Contributions

In summary, as an extension of previous studies, this study aimed at the following research objectives:

- Objective 1, assessing the impact of various demand factors on the inter-provincial transfer of ECEs in China;
- Objective 2, investigating the possibility of creating an I–O analysis system that combines HEM and CNA to evaluate differences in the characteristics of inter-provincial ECE transmission in China driven by different demand factors.

Based on the above research objectives, this study makes several contributions: (i) Inter-provincial, sectoral-level ECEs and transfers caused by different demand factors (i.e., exports, household consumption, government consumption, and capital formation) in China were calculated, and their linkage strength and spatial characteristics were examined comparatively. (ii) To overcome the inherent flaws of CMM, HEM was adopted to comprehensively account for the inter-provincial transfer of ECEs due to different demand factors and to identify key demand-side emitting sectors. (iii) Based on the CNA, an inter-sectoral transfer network of ECEs driven by different demand factors was constructed to identify key nodal sectors, transfer pathways, and industrial clusters and to describe the differences in the spatial characteristics of these networks.

Ultimately, this study establishes a multi-perspective analytical model of ECEs and their transfers based on the combination of HEM and CNA, which is expected to offer an academic basis for policymakers in crafting carbon mitigation strategies while considering different demand factors, thereby providing a foundation for decisions regarding the decarbonization of goods and services.

3. Methodology and Data

Several demand factors that constitute final demand in I–O theory are presented in Sections 3.1 and 3.2. Then, a modified HEM is introduced to decompose the ECEs into four effects (i.e., forward, backward, hybrid, and internal linkages) and estimate the ECEs of 20 industrial sectors in 31 provinces for the four demand factors in Section 3.3. At last, according to the transfer matrix of ECEs induced via different demand factors, CNA is applied to construct the inter-provincial networks of embodied carbon transfer for each demand factor in Section 3.4.

3.1. Leontief Model

The I–O model designed by Leontief allows the quantifying of the linkages between industrial sectors by constructing a monetary transfer matrix [67]. The Leontief model is shown as follows:

$$X = (I - A)^{-1} FD \tag{1}$$

where X is the total output, and I represents the identity matrix. A denotes the intermediate demand matrix, in which $a_{ij} = \frac{x_{ij}}{x_j}$ represents the proportion of direct demand of sector i from j. $(I - A)^{-1}$ stands for the Leontief inverse matrix. FD is the final demand.

Equation (2) further decomposed the final demand into four demand factors, as follows:

$$X = (I - A)^{-1}(HC + GC + CF + EX) \tag{2}$$

where HC represents household consumption in urban and rural areas. GC denotes government consumption. CF represents capital formation. EX indicates exports.

3.2. Direct Carbon Emissions Intensity

As shown in Equation (3), the direct carbon intensity of sector I can be defined as direct carbon emissions divided by total output.

$$E_i = \frac{C_i}{X_i} \tag{3}$$

where E_i is the direct carbon emission intensity of sector i, C_i is the carbon emissions directly generated via production activities in sector i, and X_i is the total output of sector i.

3.3. Hypothetical Extraction Method

The principle of HEM is to extract the target sectors from the original system and calculate the difference in carbon emissions between the original system and the new hypothetical system, where the target sector is denoted by "s" and the remaining sectors by "$-s$". The ECEs of the whole economic system are divided as follows:

$$\begin{aligned} C = \begin{bmatrix} C_S \\ C_{-S} \end{bmatrix} = \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \begin{bmatrix} X_S \\ X_{-S} \end{bmatrix} = \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \left(\begin{bmatrix} A_{s,s} & A_{s,-s} \\ A_{-s,s} & A_{-s,-s} \end{bmatrix} \begin{bmatrix} X_S \\ X_{-S} \end{bmatrix} + \begin{bmatrix} FD_S \\ FD_{-S} \end{bmatrix} \right) \\ = \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \begin{bmatrix} L_{s,s} & L_{s,-s} \\ L_{-s,s} & L_{-s,-s} \end{bmatrix} \begin{bmatrix} FD_S \\ FD_{-S} \end{bmatrix} \end{aligned} \tag{4}$$

where $C = \begin{bmatrix} C_S \\ C_{-S} \end{bmatrix}$ represents total ECE, $\begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix}$ denotes direct carbon intensity, $\begin{bmatrix} X_S \\ X_{-S} \end{bmatrix}$ represents the total output, $\begin{bmatrix} FD_S \\ FD_{-S} \end{bmatrix}$ represents the final demand, $\begin{bmatrix} A_{s,s} & A_{s,-s} \\ A_{-s,s} & A_{-s,-s} \end{bmatrix}$ denotes the intermediate demand matrix, and $\begin{bmatrix} L_{s,s} & L_{s,-s} \\ L_{-s,s} & L_{-s,-s} \end{bmatrix}$ denotes the Leontief inverse matrix.

Cella [68] assumed that the external carbon linkages of the target sector are extracted and then excluded from the import and export activities of the system. This leads to the following scenario:

$$C' = \begin{bmatrix} C'_s \\ C'_{-s} \end{bmatrix} = \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \begin{bmatrix} X_S \\ X_{-S} \end{bmatrix} = \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \left(\begin{bmatrix} A_{s,s} & 0 \\ 0 & A_{-s,-s} \end{bmatrix} \begin{bmatrix} X_S \\ X_{-S} \end{bmatrix} + \begin{bmatrix} FD_S \\ FD_{-S} \end{bmatrix} \right)$$
$$= \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \begin{bmatrix} (I - A_{s,s})^{-1} & 0 \\ 0 & (I - A_{-s,-s})^{-1} \end{bmatrix} \begin{bmatrix} FD_S \\ FD_{-S} \end{bmatrix} \tag{5}$$

where C' represents the total ECEs of the system if the target sector is excluded.

Therefore, the impact of the extracted sector on total emissions is described as follows:

$$\Delta C = C - C' = \begin{bmatrix} C_S - C'_S \\ C_{-S} - C'_{-S} \end{bmatrix}$$
$$= \begin{bmatrix} E_s & 0 \\ 0 & E_{-s} \end{bmatrix} \begin{bmatrix} L_{s,s} - (I - A_{s,s})^{-1} & L_{s,-s} \\ L_{-s,s} & L_{-s,-s} - (I - A_{-s,-s})^{-1} \end{bmatrix} \begin{bmatrix} FD_s \\ FD_{-s} \end{bmatrix} \tag{6}$$

Duarte. et al. [53] modified HEM so that carbon emissions from the extracted sectors can be further disaggregated into four components. The calculation equations are shown below:

$$IE_S = E_s (I - A_{s,s})^{-1} Y_s \tag{7}$$

$$ME_S = E_s [L_{s,s} - (I - A_{s,s})^{-1}] Y_s \tag{8}$$

$$FLE_S = E_s \, L_{s,-s} \, Y_{-s} \tag{9}$$

$$BLE_S = E_{-s} \, L_{-s,s} \, Y_s \tag{10}$$

Internal carbon emissions (*IEs*) are carbon emissions caused by the extracted sector to meet its own final demand FD_s. They can be considered local carbon emissions. Mixed carbon emissions (*MEs*) are carbon emissions generated via the repurchasing behavior of the extracted sector. In this process, the product is first exported to sectors belonging to the $-s$ region and then re-exported in these sectors to the extracted sector. Backward-linkage carbon emissions (*BLEs*) are carbon emissions resulting from the products exported by sectors in "$-s$" regions to satisfy the FD_s of the extracted sector. They reflect the ECEs flowing into the extracted sector. Forward-linkage carbon emissions (*FLEs*) are the carbon emissions induced via the export of products from the extracted sector to meet the FD_{-s} of "$-s$" regional sectors. They reflect the ECEs flowing out of the extracted sector.

NET_s reflects the net carbon emission (*NET*) of the extracted sector s, which is the difference between the *BLEs* and *FLEs* of the extracted sectors.

$$NET_s = BLE_S - FLE_S \tag{11}$$

$NET_s < 0$ it indicates that the extracted sector absorbed carbon emissions from other sectors; $NET_s > 0$ implies that the extracted sector exported carbon emissions to other sectors.

CT_s represents the flow of upstream and downstream carbon transfers involved in the extracted sector s, which is the sum of *FLEs* and *BLEs*. It can reflect the intensity of its carbon interaction with other sectors. In general, $CT > 0$.

$$CT_s = BLE_S + FLE_S \tag{12}$$

3.4. Complex Network Analysis

CNA can assess the important sectors and transfer pathways of inter-provincial carbon transfer networks and explore their spatial features through network indicators. In the I–O system, carbon emissions are embodied in the provincial and sectoral commodity flows, which constitute a complex and directional carbon transfer matrix. Based on CNA, provincial sectors are visualized as nodes of the network. The edges of the network represent the transfer of ECE. The direction of the edges denotes the source and destination of the transfer. The amount of transferred ECEs is utilized as the weight to assign values to each edge. The transfer network of ECEs can be represented using the matrix W, as follows:

$$W = \begin{pmatrix} w_{11}^{11} & \cdots & w_{1j}^{1n} \\ \vdots & \ddots & \vdots \\ w_{i1}^{m1} & \cdots & w_{ij}^{mn} \end{pmatrix} \tag{13}$$

w_{ij}^{mn} represents the transfer of ECEs from sector i in m province to sector j in n province, which is generally positive.

3.4.1. Characteristic Analysis of Nodes

In complex network theory, degree, strength, and betweenness centrality are widely applied to evaluate the characteristics of nodes [64].

1. In-degree and out-degree

The in-degree and out-degree are employed to quantify the number of edges in the network connected into and out of a given node. A higher degree of a node indicates that the node is more extensively connected to other parts of the network. It can be evaluated using the following equations:

$$K_i^{in} = \sum_{i \neq j}^{N} k_{ji} \tag{14}$$

$$K_i^{out} = \sum_{i \neq j}^{N} k_{ij} \tag{15}$$

where K_i^{in} and K_i^{out} represent the in-degree and out-degree of node i. k_{ij} are dummy variables, and $k_{ij} = 1$ indicates that there is a connected edge from node i to node j, while $k_{ij} = 0$ denotes that there is none.

2. In-strength and out-strength

The strength of a node is a weighted degree in which the weights are represented using the carbon transfer matrix W. It can be described using the following equation:

$$S_i^{in} = \sum_{i \neq j}^{N} b_{ji} \tag{16}$$

$$S_i^{out} = \sum_{i \neq j}^{N} b_{ij} \tag{17}$$

where S_i^{in} and S_i^{out} are the strength of connectivity into and out of node i, representing the in-degree and out-degree, respectively. b_{ji} denotes the amount of trade-embodied carbon transfer from node j to node i. If there is no external flow of goods at node i, then $S_i^{in} = S_i^{out} = 0$.

3. Betweenness centrality

Betweenness centrality refers to the ability of a given node in the network to influence other nodes by playing a mediating or bridging role. It can be determined by calculating the number of shortest paths for a given node divided by the total number of the shortest paths in the network. It can be described using the following equation:

$$BC_i = \frac{\sum_j^N \sum_k^N g(i)_{jk}}{g_{jk}} \tag{18}$$

where BC_i is the betweenness centrality of node i. g_{jk} represents the total amount of the shortest path between node j and node k. $g(i)_{jk}$ indicates the number of occurrences of node i in the shortest paths from node j to node k.

3.4.2. Characteristic Analysis of a Community

In complex networks, some nodes that are highly similar and closely connected will cluster together in some way. This is called a community or subdivision. There are relatively few links between different communities. The structure of community networks can be explored by assessing their internal spatial characteristics. The modular algorithm designed by Blondel. et al. [69] is utilized to find latent communities in a complex network. It can be expressed as follows:

$$Q = \frac{\sum_i^N \sum_j^N \left[b_{ij} - \left(K_i^{in} \times K_j^{out}\right) / \sum_i^N \sum_j^N b_{ij}\right]}{\sum_i^N \sum_j^N b_{ij}} \delta(E_i, E_j) \tag{19}$$

where b_{ij} means the transfer of ECEs from node i to node j. E_i indicates the latent community of node i. If $K_i^{in} = K_j^{out}$, $\delta(E_i, E_j) = 1$, or otherwise, $\delta(E_i, E_j) = 0$. The lower the modularity index, the fewer the industrial communities and the higher the industrial concentration.

3.4.3. Characteristic Analysis of a Network

In complex network theory, the average path length and the average clustering coefficient are widely utilized to access the overall characteristics of a network [70].

1. The average path length

This indicator shows the average length of the shortest path between arbitrary pairs of nodes, which can characterize the connectivity within the network. Thus, it can be expressed as follows:

$$P = \frac{1}{N(N-1)} \sum_{i \neq j}^{N} p_{ij} \tag{20}$$

where P indicates the average path length, N indicates the number of nodes in the network, p_{ij} and means the length of shortest path between node i and j, which means the number of edges.

2. The average clustering coefficient

This indicator reflects the probability that the arbitrary pair of adjacent nodes to a given node is also linked, which can also be expressed as the average frequency of occurrence of triangular node clusters. It is able to measure the degree of aggregation of complex networks. It can be calculated as follows:

$$C = \frac{1}{N} \sum_{1}^{N} \frac{2d_i}{c_i(c_i - 1)} \tag{21}$$

where C indicates the average clustering coefficient, c_i is the number of nodes associated with the given node i, and d_i means the number of edges linked to node i.

Complex networks can be categorized into three types, depending on their characteristics: regular, random, and small-world networks. The average path lengths and average clustering coefficients are relatively large for regular networks, while random networks are the exact opposite. A small-world network has a topological structure between those of the first two, and it is closer to the network that exists in the real world [59].

3.5. Data Sources and Processing

The various sources of data utilized in this study include currency I–O tables, carbon emission inventories, population, import, and export amounts, and GDPs. Specifically, the multi-regional I–O tables and provincial carbon dioxide emission inventories for China in 2017 were collected from China Emission Accounts and Datasets [71]. Data on populations, import and export amounts, and GDPs by province were obtained from the China Statistical Yearbook [72]. However, there were some disparities in the sectoral categorization of these datasets. To address such discrepancies, the sectoral classification of this study needed to be adjusted. Based on previous studies [24,34,66,73], the industrial sectors were integrated into 20 sectors. The code of the aggregated sectors and the provinces are presented in Tables 1 and 2, respectively. To simplify the expression, "The construction sector in Beijing" will be abbreviated as "BJ17" in this study, and the expression of the sector in other provinces follows this convention. In general, Figure 1 illustrates the assessment framework of this study.

Table 1. Abbreviations for China's 31 provinces in 2017.

Province	Abbreviation	Province	Abbreviation
Beijing	BJ	Hubei	HB
Tianjin	TJ	Hunan	HN
Hebei	HE	Guangdong	GD
Shanxi	SX	Guangxi	GX
Inner Mongolia	NM	Hainan	HI
Liaoning	LN	Chongqing	CQ
Jilin	JL	Sichuan	SC
Heilongjiang	HL	Guizhou	GZ
Shanghai	SH	Yunnan	YN
Jiangsu	JS	Tibet	XZ
Zhejiang	ZJ	Shaanxi	SN
Anhui	AH	Gansu	GS
Fujian	FJ	Qinghai	QH
Jiangxi	JX	Ningxia	NX
Shandong	SD	Xinjiang	XJ
Henan	HA		

Table 2. Aggregated sector codes for 2017.

Code	Aggregated Sector
1	Farming, Forestry, Animal Husbandry, Fishery and Water Conservancy
2	Mining Industry
3	Manufacture of Foods and Tobacco
4	Manufacture of Textiles and Clothing
5	Processing of Woods and Furniture
6	Manufacture of Papermaking, Printing, and Paper Products
7	Processing of Petroleum, Coking, and Nuclear Fuel
8	Chemical Industry
9	Manufacture of Nonmetal Products
10	Manufacture of Metal Products
11	Manufacture of General Machinery
12	Manufacture of Special Machinery

Table 2. *Cont.*

Code	Aggregated Sector
13	Manufacture of Transport Equipment
14	Manufacture of Electrical Machinery and Electronic Equipment
15	Manufacture of Instruments, Meters, and Other
16	Electric Power, Gas, and Water Production and Supply
17	Construction
18	Wholesale, Retail Trade, and Accommodation
19	Transport, Storage, and Post
20	Other Services

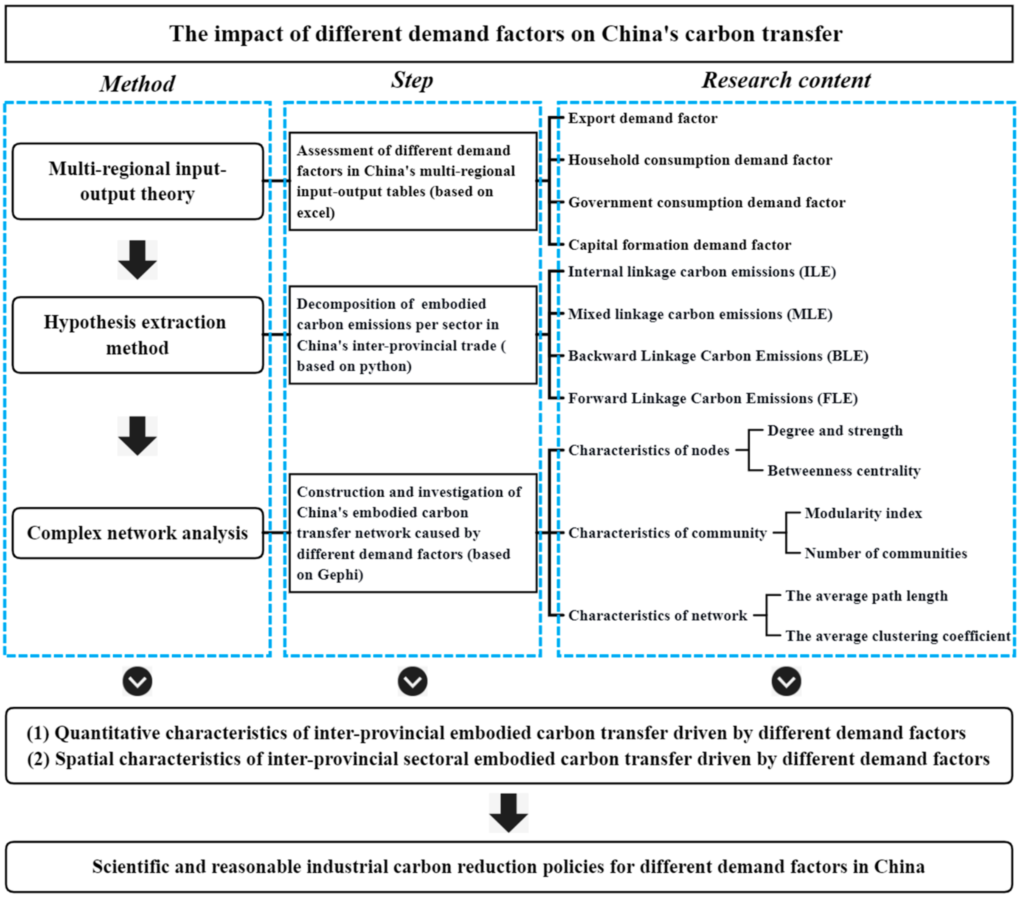


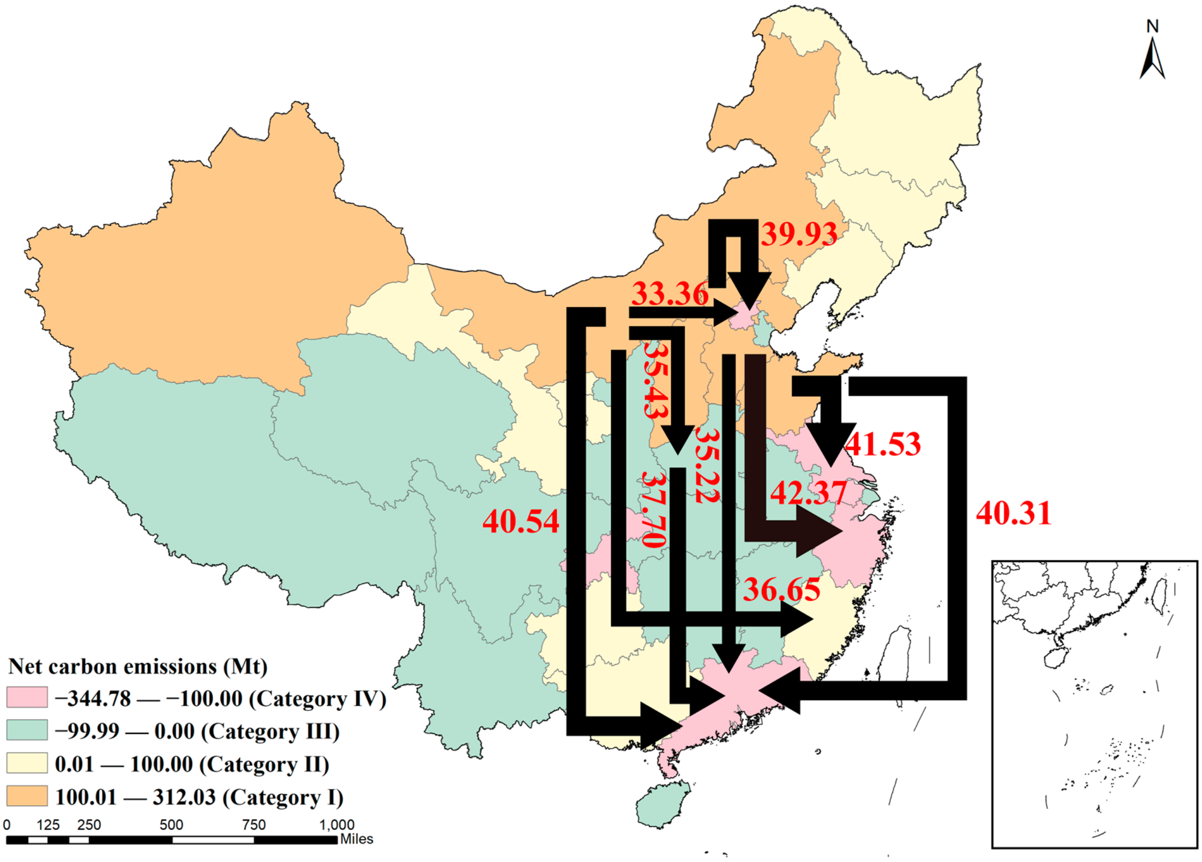
Figure 1. The theoretical framework of this study.

4. Result

4.1. Analysis of Carbon Emissions and Transfers Caused by the Final Demand

4.1.1. Overall Characteristics

The calculation results of the sector-level hypothesis extraction method were organized according to the administrative divisions of China. Figure 2a,b shows the detailed data of carbon flows by province in China during 2017. The spatial distribution of China's provincial NET is shown in Figure 2a, along with the top ten inter-provincial trade-embodied carbon transfer pathways. According to the NET of each province, they can be categorized into four groups: Category I, whose NET > 100 million tons (Mt), Category II ($0 \leq$ NET < 100 Mt), Category III (0 > NET ≥ -100 Mt), and Category IV (NET < -100 Mt). Figure 2b reveals more sectoral-level details of inter-provincial carbon transfers. The provinces were arranged in order of NET from lowest to highest, where the sectoral composition of carbon inflows and carbon outflows is shown on the left and right, respectively.



(**a**)

(**b**)

Figure 2. (**a**) Net carbon emissions by province and major inter-provincial embodied carbon transfer pathways driven by final demand in China in 2017. (**b**) Sectoral composition of inter-provincial embodied carbon transfers driven by final demand in China in 2017.

Figure 2a,b reveals the macroscopic characteristics of carbon transfer in China, for which several findings were observed. Firstly, the macro direction of the carbon emission transfer was from the resource-rich north to the trade-developed south of China. The resource-rich northern provinces were Category III and IV areas with net carbon outflows (e.g., Inner Mongolia and Shanxi), while the trade-developed central and southern provinces were Category I and II areas with net carbon inflows (e.g., Guangdong and Zhejiang). Secondly, the largest trade-embodied inter-provincial carbon transfer pathway was from Hebei to Zhejiang (42.37 Mt), followed by Shandong to Jiangsu (41.53 Mt), Inner Mongolia to Guangdong (40.54 Mt), Shandong to Guangdong (40.30 Mt), and Hebei to Beijing (39.03 Mt). Thirdly, from a sectoral perspective, carbon-intensive sectors such as Sectors 16, 10, and 9 were the main contributors to trade ECEs. As shown in Figure 2b, Sector 16 was responsible for the most carbon emissions with 2050.14 Mt, accounting for 55.63% of the total ECEs, followed by Sector 10 with 639.17 Mt (17.34%) and Sector 9 with 269.87 Mt (7.32%).

In detail, for the province classification, there were four main findings:

1. The Category I provinces in China were mainly located in coastal areas or served as the hub of the country's commodity trade, including Guangzhou, Zhejiang, and Beijing. Among these provinces, Guangdong was the most typical and important Category I province, receiving four of the top ten inter-provincial trade-embodied carbon transfer pathways and contributing about 33.73% (153.78 Mt) of the province's total carbon imports. Figure 2b shows that Sector 16 was the main contributor to Guangdong's imported carbon emissions (251.46 Mt), followed by Sector 10 (87.59 Mt) and Sector 9 (37.65 Mt). The rapid development of Guangdong's automobile, electronics, and petrochemical industries has severely tested the resource-carrying capacity of its ecological environment. The huge demand and limited resources have led Guangdong's enterprises to outsource carbon-intensive production and services to other regions, which is common among Category I provinces. However, the regions accommodating industrial transfer would generate substantial carbon emissions and, thus, bear a disproportionate share of liability for emissions reduction, which is unfair to production-oriented regions. Moreover, Beijing, the capital and commercial center of China, was the only non-coastal Category I province that was the destination of two major inter-provincial transfer pathways, with its NET second only to those of Guangdong and Zhejiang (−200.62 Mt). The booming services and logistics industry in Beijing is driven by household consumption and business activity, but this has also led to its dependence on carbon-intensive products from inland provinces;
2. The Category II and III provinces were mainly engaged in primary and secondary industries (the manufacturing of intermediate products), which require a large amount of both imports and exports. Henan was representative of such provinces and is the only Category III province in Figure 2a that is both the destination and source of top-ten carbon pathways. In detail, Henan absorbed 35.43 Mt of carbon emissions from Inner Mongolia and transferred 37.70 Mt to Guangdong, while its own NET was only 32.24 Mt. Figure 2b provides further details on the sectoral carbon emissions in Henan. It imported 184.45 Mt and 36.69 Mt from the Sector 16s and Sector 10s of other provinces, while it exported 105.18 Mt, 45.52 Mt, 41.24 Mt, 20.14 Mt, and 15.8 Mt from Sectors 16, 10, 9, 2, and 19, respectively. With industrial upgrading, Category I provinces have gradually abandoned some heavily polluting industries. However, these industries have been transferred to the central and northern provinces due to the continued demand for products from Sectors 14 and 17. The developed industries of these provinces provide the necessary intermediate products for the southern provinces. But they also import large quantities of energy and materials from the interior for further processing, which significantly increases their ECEs. Overall, the pressure on these production-based provinces to achieve their policy targets for carbon reduction is serious. To efficiently achieve carbon reduction targets, policymakers should consider the impact of industrial production and consumption on ECEs in

different locations when allocating carbon mitigation responsibilities. In addition, not only should Category I provinces reduce the utilization of carbon-intensive products but Category II and III provinces, such as Henan, should also be subsidized for the application of low-carbon technologies and minimization of carbon emissions;

3. Based on the study of NET and sectoral carbon emissions, the Category IV provinces were categorized into two groups: resource-based and resource-processing compound provinces. The resource-based provinces are rich in mineral resources and fossil energy, including Xinjiang and Inner Mongolia. Inner Mongolia was the largest province in China in terms of carbon outflow, at about 367.89 Mt. IM16 was responsible for 306.15 Mt of carbon emissions transfers, or 83.22% of the total. This not only indicates that the development of this category of provinces is heavily dependent on the export of low-value-added resources but also reveals the dominance of the energy sector in China's carbon transfer. The resource-processing compound provinces included Hebei, Shanxi, and Shandong, whose Sector 10 and Sector 9 contributed more significantly to carbon emissions. For example, HE10 contributed 173.78 Mt in carbon transfers, accounting for 53.38% of its total carbon outflow. These provinces have well-developed metal and non-metal manufacturing industries that provide raw materials for industries such as automobiles, electronic equipment, and construction in the central and eastern provinces. However, this development model results in serious carbon emission problems. Coordinating the development and carbon reduction of such provinces is a challenge that policymakers need to consider. Reducing pollution due to production and increasing the added value of products are extremely important for Category IV provinces. In addition, the allocation of responsibility for carbon mitigation needs to take due account of the contribution from production and consumption regions.

4.1.2. Multiple Indicators of Provincial Carbon Emissions

To deeply analyze the relationship between ECEs, imports/exports, and populations in each province, the scatter plots of provincial indicators for China were mapped. Considering the practical economic significance, the average carbon emission intensity of imports and exports, and the carbon flow per capita were chosen as the main indicators. As shown in Figure 3, it was found that the carbon intensity of each province differed under various analysis perspectives. The main findings were listed as follows.

First, the average ECEs of exported products increased significantly from the Category I to the Category IV provinces (Figure 3a), which reflected the essential differences in the export structure of different provinces. For instance, the average embodied carbon emission of domestic trade was 1.26 t $CO_2/10^4$ RMB in 2017. However, the average ECEs of exports from Category I and Category II provinces such as Beijing (0.21 t $CO_2/10^4$ RMB), Shanghai (0.38 t $CO_2/10^4$ RMB), and Guangdong (0.40 t $CO_2/10^4$ RMB) were generally lower than the domestic average. The probable reason is that such provinces are mainly engaged in high-tech industries and service industries, resulting in a lower carbon emission intensity of their export products. However, due to the prosperity of manufacturing, the average embodied carbon emission of Jiangsu (0.74 t $CO_2/10^4$ RMB) and Zhejiang (0.57 t $CO_2/10^4$ RMB) was relatively high. On the other hand, the Category IV provinces were dominated by resource extraction and heavily polluting industries, such as Shanxi (3.76 t $CO_2/10^4$ RMB) and Inner Mongolia (4.62 t $CO_2/10^4$ RMB). The imperative for such provinces is to reduce their dependence on heavily polluting industries and enhance their production efficiency in key products such as energy and metals, thereby enhancing the value added from their exports to achieve a low-carbon industrial transformation.

Second, as shown in Figure 3b, the provincial average ECEs were more equal in terms of imports than in terms of exports. The distribution of scattered points was the opposite, with a gradual decrease from Category I to Category IV. Figure 3a,b reveals that the Category I provinces import substantial quantities of low-value-added energy and minerals from Category IV provinces, which are then re-processed into products such as mechanical and electronic equipment for export to other provinces. However, the proportion of carbon-intensive products imported by Category I provinces was higher, which led to a larger average embodied carbon emission from their imports. The distribution of the scattered points was slightly skewed downward to the lower right. In summary, it is crucial to emphasize the coordinated regional management of carbon emissions to avoid the carbon spillover effects caused by the industrial transformation in developed provinces. For instance, developed provinces should take some responsibility for the additional carbon emissions from the provision of mineral products in other regions. Controlling the carbon intensity of inter-provincial carbon transfers should be a common concern for both the supply side (e.g., Inner Mongolia and Hebei) and the consumption side (e.g., Beijing and Guangdong).

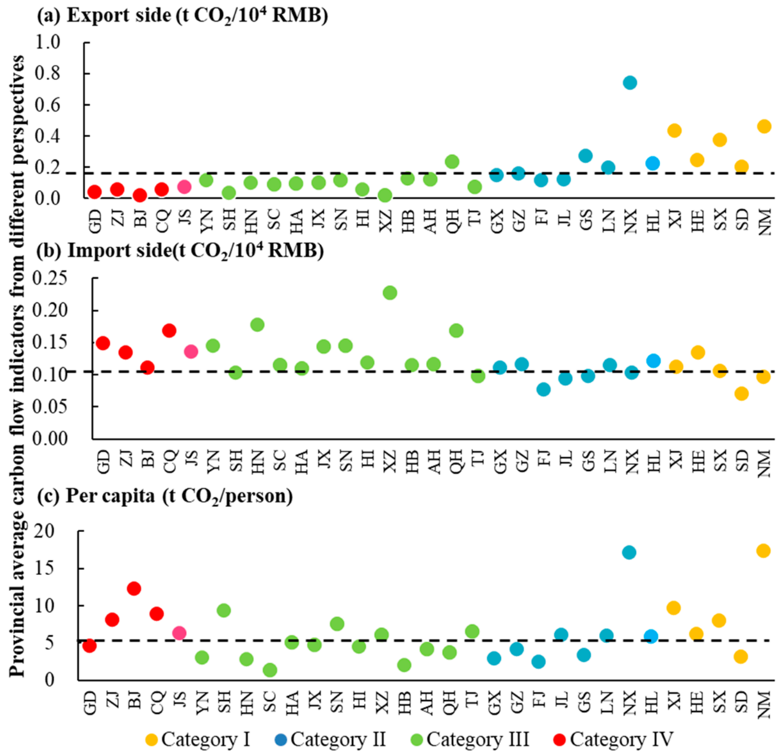


Figure 3. Average carbon flow indicators by province in China from (**a**) the export side, (**b**) the import side, and (**c**) the per capita side.

Third, the distribution of carbon flows per capita was found to be more average and disorderly compared to the average carbon flows of imports and exports (Figure 3c). This result reflects that the inequality caused by the import/export trade was greater than that caused by the population in China's carbon transfer. Beijing had the highest carbon flow per capita at 12.34 tons/person among Class I provinces, followed by Chongqing and Zhejiang. This indicates that Beijing's developed economy and booming trade have caused its enterprises and residents to create a large amount of carbon emissions. Continuing to promote industrial upgrading and high-quality development in such regions is significant for reducing per capita carbon flows. Furthermore, Inner Mongolia ranked first among all provinces with a per capita carbon flow of 17.42 tons/person, followed by Ningxia (17.22 tons/person). These provinces are sparsely populated but rich in natural resources and developed in heavy industry, leading to excessive per capita carbon flows. To solve this problem, the utilization of clean sources (e.g., solar and wind energy) and the promotion of low-carbon industries (e.g., services and information technology) should be encouraged to reduce carbon pollution.

In conclusion, it is essential for Chinese policymakers to recognize the inequality of ECEs and transfers in terms of geographical distribution and per capita and take appropriate measures to reduce carbon emissions in each province. The Category III and IV provinces (e.g., Inner Mongolia) should enhance their proportion of clean energy to reduce the carbon pollution caused by fossil energy consumption and develop high-value-added industries to improve economic efficiency. On the other hand, Category I and II provinces, such as Guangdong, Zhejiang, and Beijing, should strengthen communication and cooperation with the key emitting sectors of their trading partner provinces. By imposing a carbon tax on carbon-intensive products in key sectors and subsidizing the research and application of low-carbon production models, the embodied carbon intensity of inter-provincial trade can be effectively reduced.

4.2. Analysis of Carbon Emissions and Transfers Driven by Different Demand Factors

To further analyze and explore the characteristics of carbon transfer by different demand factors, this study divided the final demand into four factors (i.e., exports, household consumption, government consumption, and capital formation) and separately investigated the effects of the different demand factors on the embodied carbon transfer among provinces. Figure 4 illustrates the provincial NET and inter-provincial embodied carbon transfer pathways induced via the four demand factors. The categories with varying levels of net carbon emissions were marked with corresponding colors, as shown in the legend.

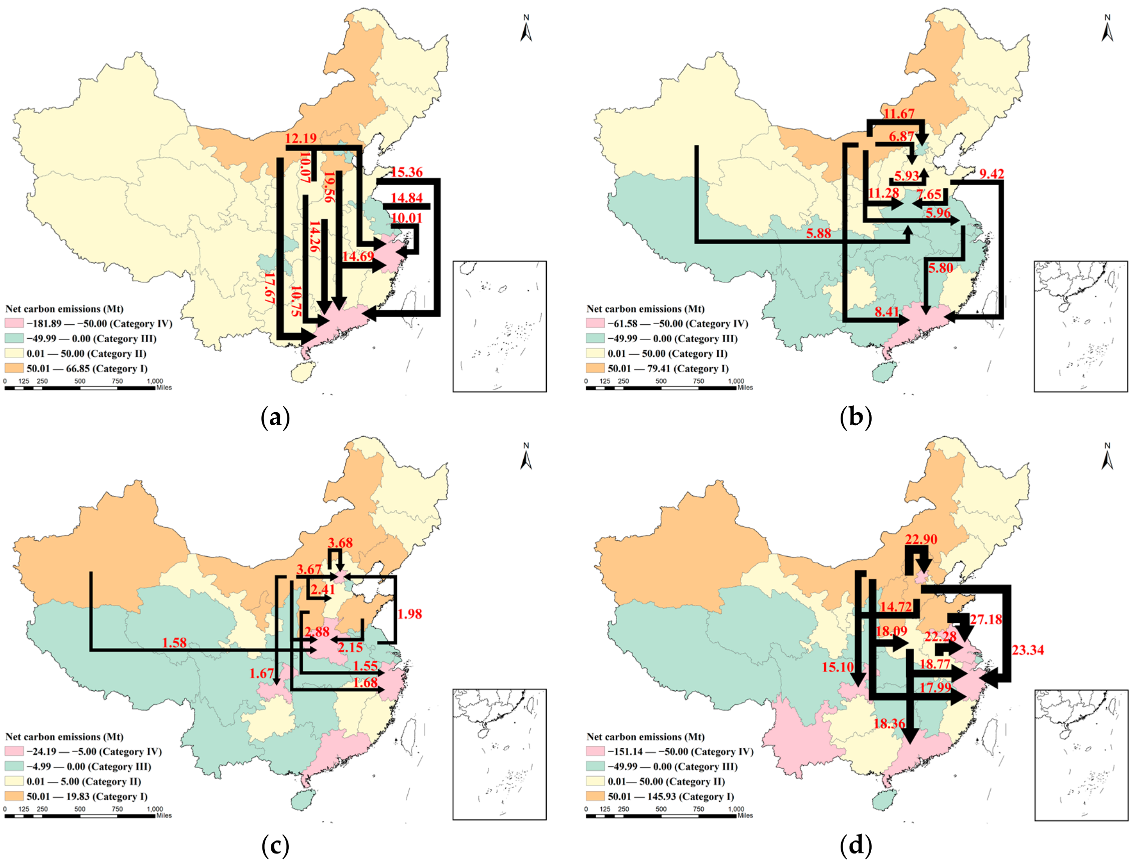


Figure 4. Embodied carbon transfer pathways and net carbon emissions among provinces in China induced via different demand factors, such as (**a**) exports, (**b**) household consumption, (**c**) government consumption, and (**d**) capital formation.

4.2.1. Overall Characteristics of Different Demand Factors

In general, the macro characteristics of carbon transfers induced by different demand factors in China were essentially similar, and carbon emissions were embodied in commodity trading, moving from resource-based provinces in the north to industrial-based provinces in the middle and east, but there were significant differences in terms of quantity and path. Specific to each demand factor, the macro findings were summarized as follows: (i) Capital formation. The carbon transfer caused by capital formation ranked first, at 2062.92 Mt, accounting for 55.98% of the total inter-provincial carbon transfer in 2017. This indicated that capital formation was the dominant influencing factor of embodied carbon transfers. (ii) Exports. The destination of the carbon transfer caused by exports was highly concentrated, with six of the top ten inter-provincial carbon transfer paths pointing to Guangdong, such as Hebei to Guangdong (19.56 Mt), Inner Mongolia to Guangdong (17.67 Mt), Shandong to Guangdong (15.36 Mt), etc. The remaining four pointed to Zhejiang, such as Hebei to Zhejiang (14.69 Mt) and Inner Mongolia to Zhejiang (12.19 Mt). Guangdong and Zhejiang, as important coastal cities in China, have numerous ports and industrial bases and are pivotal in international and domestic trade. This has led to a highly concentrated export structure and increased environmental pressure on such export-oriented provinces. (iii) Household and government consumption. The carbon transfers from household and government consumption were more fragmented and complex than the other factors. For example, the top ten carbon transfer pathways from household consumption were significantly smaller than those of exports (Figure 4a,b), but household consumption (729.64 Mt) was larger than exports (686.29 Mt) in terms of total carbon transfers. This suggests that, in addition to the top ten carbon transfer pathways in the figure, the remaining carbon transfers from household consumption were much larger in total. The management of such carbon emissions and transfers associated with household and government consumption is a complex issue for policymakers to address.

4.2.2. Sectoral Carbon Transfer for Different Demand Factors

Figure 5 complements the top twenty trade-embodied carbon transfer pathways among sectors with different demand factors. Based on the results in Figures 4 and 5, the transfer of ECEs due to different final demands exhibited the following characteristics.

First, the ECEs resulting from exports were concentrated in key provinces and sectors. Guangdong, as the center of industrial production and trade in China, absorbed 197.92 Mt of ECEs driven by export factors, accounting for 28.84% of the carbon transfers caused by exports. Among them, GD14 accounted for 39.39% of its total carbon emissions caused by exports, at 77.95 Mt. Similarly, in Zhejiang, ZJ14 received 128.17 Mt (18.68%) of the embodied carbon transfers. The sector-level transfer analysis revealed that Sector 14 in southern provinces is the main carbon importer, while Sector 16 and Sector 10 in resource-based provinces are carbon exporters (Figure 5a). Among them, HE10 transferred 5.34 Mt of carbon emission to GD16, followed by IM16 to GD14 (5.11 Mt). As key participants in the "Belt and Road", Guangdong and other coastal provinces will continue to strengthen their bilateral trade cooperation with foreign countries in the future. This will induce a sustained growth of ECEs from exports, bringing additional pressure to the promotion of the national carbon reduction strategy. Therefore, the export-oriented sectors represented by GD14 and ZJ14 should reduce their reliance on metal products and electricity and continuously update their production technologies to reduce their carbon emission intensity. Meanwhile, decision-makers need to prudently plan the development direction of the industry to balance the development of the export trade and the national carbon reduction strategy.

Second, the provincial NET attributable to household consumption is characterized by a clear north–south disparity with a stepwise distribution. The carbon transfer pathways mostly terminated in provinces with thriving urban economies (Figure 4b). For instance, Inner Mongolia (−79.41 Mt), Shanxi (−47.28 Mt), and Xinjiang (−39.30 Mt) in the north provided a substantial number of carbon-intensive products to Guangdong (61.58 Mt) and Henan (45.97 Mt) to meet surging urban demand. As shown in Figure 5b, IM16 and SD16 contributed a substantial carbon transfer to meet the demand of Sector 16 and Sector 10 in provinces such as Guangdong and Beijing. Notably, the manufacture of foods and tobacco in Henan (HA3) absorbed 2.39 Mt and 1.47 Mt from IM16 and SD16, respectively. This indicated that the potential for emission reduction in the food-processing industry should not be underestimated. With the boom of the urban economy, the ECEs resulting from household consumption will increase significantly [40,74]. Therefore, a green and clean lifestyle should be advocated for to reduce household-related ECEs. Considering the inequality in incomes and carbon in household consumption, the carbon mitigation potential of different income groups should also be considered.

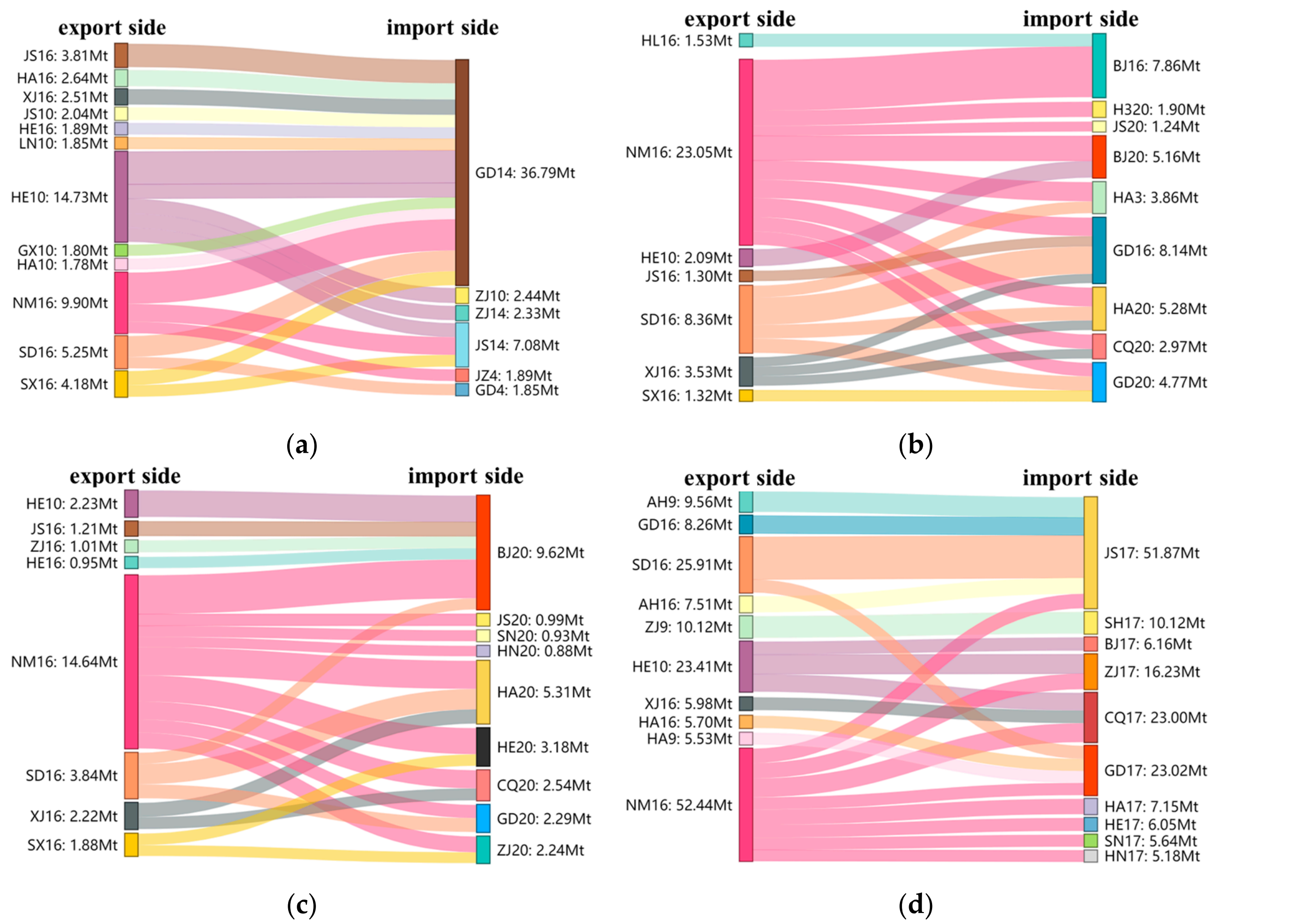


Figure 5. The top 20 inter-provincial embodied carbon transfer pathways in China caused by different demand factors, such as (**a**) exports, (**b**) household consumption, (**c**) government consumption, (**d**) and capital formation.

Third, government consumption had the lowest embodied carbon transfers among several demand factors, accounting for only 206.25 Mt (5.60%). The carbon transfer destinations were mainly developed provinces, such as Beijing (24.19 Mt), Henan (11.42 Mt), and Zhejiang (8.41 Mt), which were similar in household consumption. However, the ECEs due to government consumption were concentrated completely in Sector 20 (Figure 5c). Specifically, the demand for government consumption for the service sectors of the internet, finance, real estate, research, education, culture, and public administration caused significant carbon emissions. Among them, BJ20 was the most important driver (9.63 Mt), reflecting the extensive government functions and thriving service sector that Beijing has as the capital of China. And IM16 was the most important energy supply sector for government consumption (14.66 Mt). As the main provider of social welfare, the government is not only responsible for ensuring basic livelihoods but also plays a fundamental role in the economy and carbon emission system. Therefore, the government should embrace the principle of sustainable development, provide low-carbon public services, and reduce the impact of government consumption on carbon emissions.

Fourth, capital formation had the greatest influence on carbon transfer, and it was mainly directed to the economic centers (Figure 4d). Figure 5d indicates that Sector 17 contributed the most to ECEs due to capital formation. For example, carbon inflows caused by the construction industry accounted for 58.59% in Zhejiang, 77.66% in Chongqing, and 61.38% in Guangdong. This was mainly due to the significant demand for metallic (e.g., steel and iron) and non-metallic products (e.g., cement, glass, and ceramics) in the construction process, as these products are carbon-intensive. In China, the most important manifestation of capital formation is the construction of new infrastructure. With the steady progress of the 14th Five-Year Plan, China's economy is entering a new phase of development, and the demand for new infrastructure (e.g., the industrial IoT, extra-high voltage grids, charging piles, big data centers, etc.) will further expand. Therefore, the government should fully assess the potential implications of infrastructure construction on the ecological system and encourage the elimination of carbon-intensive building materials in the construction industry to reduce ecological pollution.

4.2.3. The Interval Distribution of Carbon Transfer under Different Demand Factors

To further investigate the characteristics of the carbon transfer caused by different demand factors, this study counted the carbon intensity of sectors that provide products for the provincial industrial chain and inter-provincial trade and evaluated their cumulative carbon emissions in intervals of different carbon intensity. As shown in Table 3, the sectors were grouped into Class I to Class VI according to intervals of carbon intensity. On this basis, Figure 6 shows the cumulative emissions and their proportions for sectors in Class I to Class VI, driven by the four demand factors.

Table 3. Sectoral classification of China in 2017 based on carbon intensity.

Classification	Intensity of Carbon Emissions (t CO_2/104 RMB)
Class I	0.00–0.99
Class II	1.00–4.99
Class III	5.00–9.99
Class IV	10.00–14.99
Class V	15.00–19.99
Class VI	20.00–24.99

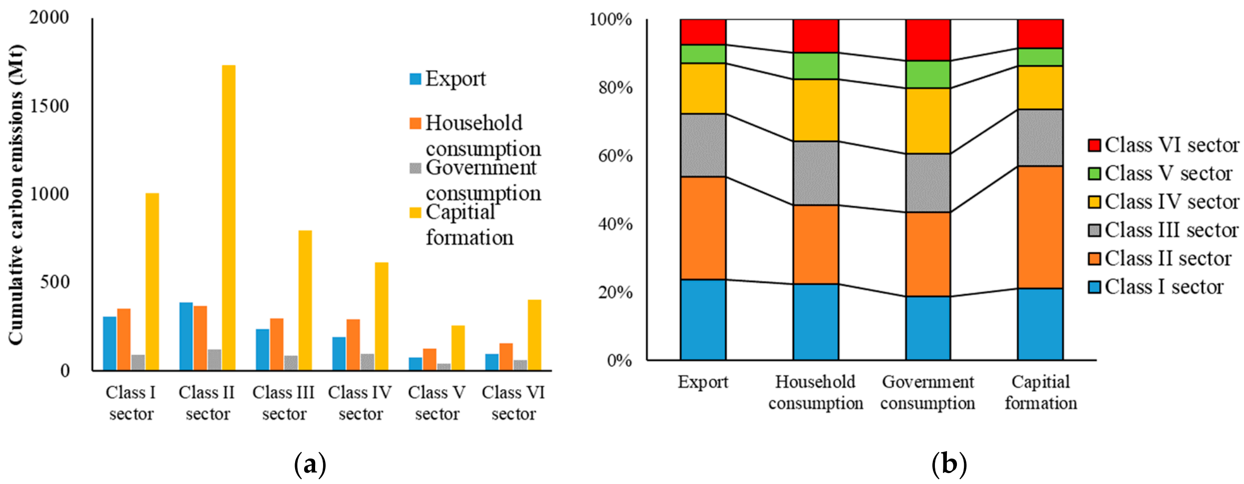


Figure 6. Interval distribution of embodied carbon emissions at different carbon intensities, driven by various demand factors: (**a**) quantity; (**b**) proportion.

As shown in Figure 6, there was a significant difference among the different demand factors, and the main findings were as follows: First, the distribution of the cumulative carbon emissions of all demand factors presented the characteristics of higher middle and lower ends (Figure 6a). Among all demand factors, the Class II sector was the main contributor to ECEs with 386.70 Mt, 366.94 Mt, 119.82 Mt, and 1734.26 Mt, respectively, followed by the Class I sector. This indicated that although light industry had a low carbon intensity, it was still a major source of carbon emissions. In addition, there was an unexpected rise in cumulative carbon emissions for the Class VI sector, which may be attributed to high-polluting sectors in some provinces. These high-polluting sectors (i.e., Classes V and VI) had a much higher carbon intensity than the same sectors in other provinces and should be identified and strictly limited.

Second, the ECEs induced by household consumption were larger than those due to exports in all sector classes, except for the Class II sector (366.94 Mt and 386.70 Mt). Figure 6b shows that the household-consumption-related ECEs in the Class I and Class II sectors accounted for 22.32% and 23.14% of the total, respectively, which were lower than those caused by exports at 23.69% and 30%. However, the proportion of carbon emissions resulting from the Class IV sectors for household consumption was 18.29%, higher than that of 14.79% for exports. This indicated that household consumption was more reliant on high-carbon products and had a lower demand for low-carbon products.

Third, government consumption had the highest proportion of demand for carbon-intensive products (produced in Class IV, V, and VI sectors), with 19.12%, 7.99%, and 12.23%, respectively. In contrast to other demands, it had more cumulative carbon emissions in Class IV than in Class III (92.80 Mt and 83.59 Mt). Therefore, government departments should limit the procurement of high-carbon products and increase subsidies for cleaner products in order to reduce the ECEs generated by the provision of social benefits.

Fourth, capital formation had the highest total cumulative ECE, but its demand for carbon-intensive products was relatively low. The highest share of its ECEs was for Class II products at 36.07% (1734.26 Mt), followed by Class I products at 20.95% (1007.28 Mt). Policymakers should focus on developing carbon reduction policies for the light industry.

4.3. Complex Network Analysis for Different Demand Factors

In order to deeply investigate the inter-provincial sectoral-level carbon transfers influenced by different demand factors, CNA was adopted to assess their spatial characteristics and clustering features. A complex network of carbon transfers in China was constructed based on the hypothesis extraction method while considering various demand factors.

4.3.1. Overall Network Characteristics of Different Demand Factors

The original carbon transfer network for different demand factors contained 620 nodes and 384,400 edges in 31 provinces. The screening of the original nodes and edges was necessary because some carbon transfer pathways were ineffective or too small to be of practical significance. The threshold value of the carbon transfer pathway was set to one ton, and the pathways were classified into three categories: effective pathways (FLEs $\geq$ 1 t), weakly effective pathways (0 < FLEs < 1 t), and ineffective pathways (FLEs = 0). An effective pathway represents the actual existence of a strong carbon linkage between two sectors. A weak efficient pathway illustrates the existence of a carbon linkage between the two sectors, but it is weak. An ineffective pathway indicates that the two sectors are not linked in the carbon emission system. Figure 7 illustrates the quantitative composition of the carbon transfer pathways for four demand factors.

The following main findings emerged: (i) Household consumption had the largest number of effective pathways at 263,367, which indicated that the overall sophistication of the carbon transfer network induced by household consumption was the highest. (ii) Government consumption had 329,039 weakly effective pathways, accounting for 85.74% of all its paths, which was much higher than the other demand factors. Due to the existence of many weakly effective pathways for carbon transfer, government consumption has maintained links with many industries even though the carbon impact of this linkage was weak. (iii) Exports induced the largest number of inefficient pathways for carbon transfer at 47,607, suggesting that there were many sectors not involved in export-related carbon transfer. This result reflected the high concentration of industries related to export demand factors, which was consistent with Section 4.2.2. (iv) The network related to capital formation had 253,158 effective pathways and 33,599 ineffective pathways, both of which were ranked second among the four demand factors. The carbon transfer networks linked by capital formation were high in complexity and concentration, with a closer exchange of products and services between sectors.

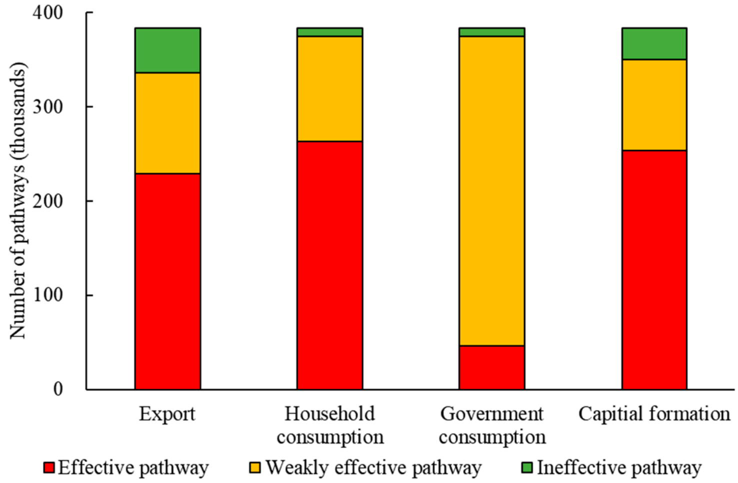


Figure 7. The number of different types of carbon transfer pathways driven by different demand factors.

In a trade network, economic sectors must exchange goods with the outside to meet their own and other sectors' final demands, thereby achieving coordinated industrial development. As such, the importance of trade networks can be characterized by indicators such as the number of nodes, the intensity of interaction, and spatial and cluster relationships. Table 4 shows the key network characteristics of the complex network induced by different demand factors, and the main findings were as follows: (i) First, the capital-formation-related network had an average degree of 581.820, ranking first. Moreover, the weighted degree of the capital-formation-related network was about 7,854,414, exceeding the sum of the other demand factors. This indicated that capital formation drove an extremely large number of industrial sectors, and it was the dominant player in embodied carbon transfers. (ii) Second, the networks related to capital formation had the lowest average path length (1.043) and the highest clustering coefficient (0.958), which was consistent with the findings in Section 4.2.2. Notably, the average clustering coefficient of export-related networks was low (0.855), similar to government consumption (0.834), which had fewer effective carbon transfer pathways. This indicated that there are many relatively independent carbon-emitting sectors in the export-related network that need to be attended to by policymakers. (iii) Third, the capital-formation-related network had the lowest degree of modularity (0.424) with 13 industrial communities, indicating that it had the strongest inter-sectoral carbon linkages. In contrast, the government-consumption- and household-consumption-related networks were characterized by a higher modularity coefficient and more industrial communities, suggesting that such networks were more loosely connected and lacked dominant sectors.

Table 4. Network indicators for carbon transfer networks for different demand factors in China in 2017.

	Export	Household Consumption	Government Consumption	Capital Formation
Average Degree	514.054	574.822	108.455	581.820
Average Weighted Degree	2,096,105	2,595,078	796,931	7,854,414
Average Path Length	1.058	1.045	1.117	1.043
Average Clustering Coefficient	0.855	0.949	0.834	0.958
Modularity Index	0.455	0.536	0.523	0.424
Number of Communities	13	15	25	13

4.3.2. Complex Network Analysis of Carbon Transfer

In order to explore the spatial features of the ECE transfer network and locate the crucial betweenness sectors for different demand factors, this study visualized the complex network based on Gephi 0.10.2 software. Due to the large number of nodes and pathways in each network, further screening of the nodes was necessary in the study to identify the important nodes that contributed to the overall network. The weighted degree indicates the strength of the connection between nodes and is appropriate as a screening metric. Figure 8 illustrates the social network consisting of the top twenty nodes based on the weighted degree for different demand factors. Each node represents a crucial sector. The betweenness centrality of a node determines its size. The larger the circle of a node, the more significant its connecting role in the network. Nodes were color-coded according to their industrial communities obtained from the modular algorithm, and nodes of the same color belonged to the same industrial community. The edges stand for transfers of ECEs, and their width represents the amount of such transfers. The color of the edge was determined by the color of the source node. The main findings were as follows.

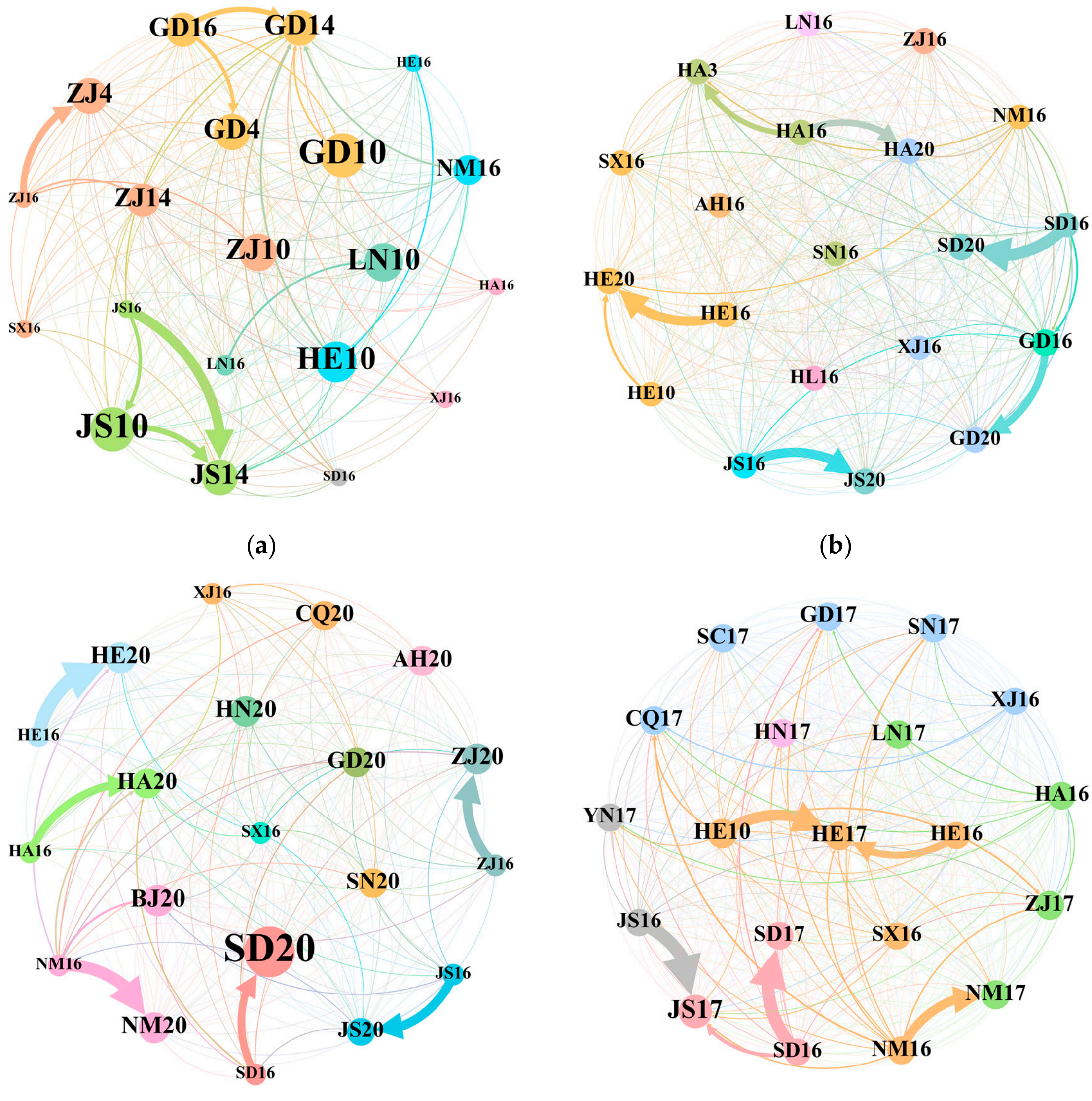


Figure 8. The embodied carbon transfer network caused by different demand factors, such as (**a**) exports, (**b**) household consumption, (**c**) government consumption, and (**d**) capital formation in China in 2017.

1. Exports

As shown in Figure 8a, the export-induced carbon transfer network was dominated by several important industry communities, which were mostly dominated by provincial sectors. This indicated that the provincial industrial chain had a significant impact on export-related carbon transfers. The largest industrial community, comprising 26.99% of all nodes, was represented by the orangish community, which consisted of the manufacture of textiles and clothing (Sector 4), Sectors 10, 14, and 16 in Guangdong. Notably, the orange-red (represented by ZJ14) and light green (represented by JS14) communities exhibited highly similar network structures to the orangish communities, with carbon transfer pathways for Sectors 16–10 and 16–14. This suggested that Sectors 14 and 10 play key driving roles in the export-related network, which was consistent with the findings in Section 4.2. As China's foreign trade hubs, the economies of coastal provinces (e.g., Guangdong, and Zhejiang) are heavily reliant on exports, but their highly concentrated industrial structures have resulted in intensive environmental pollution. Therefore, policymakers need to consider industrial carbon reduction strategies that address export demand.

In addition, the industrial community represented by HE10–HE16–NM16 (colored light blue) and HA16–XJ16 (colored pink) was distinct from the former, as its main sectors came from different provinces and were dominated by Sector 16 in the inland provinces. This type of community provided a significant amount of carbon-intensive energy products for downstream production located in other provinces.

From the sectoral perspective, Sectors 4, 10, and 14 exhibited high betweenness centrality, while Sector 16 tended to have low betweenness centrality in each province. This indicated that the former played a more significant role as a mediating sector in the carbon transfer network. For example, Sector 10 required raw materials and energy in its production process to make metal products, which were then exported to downstream industries such as Sector 14. Therefore, the government should scientifically assess the demand for upstream and downstream products in intermediary sectors such as textile manufacturing, metal product manufacturing, and electronic equipment manufacturing and subsidize these sectors to develop cleaner production technologies to reduce overall carbon emissions.

2. Government consumption and household consumption

In terms of complex networks, the carbon transfer networks caused by government consumption and household consumption shared some similarities (Figure 8b,c). First, there were more communities of government consumption and household consumption than exports, and the small communities formed by the nodes were more dispersed. The provinces that were well traded tended to have separate industrial communities, which was consistent with the results in Section 4.2. Second, the carbon transfer network related to government consumption and household consumption was dominated by a pathway pointing from Sector 16 to Sector 20. This indicated that the services industry was the main area where consumption behavior occurred and that it consumed a large amount of carbon-intensive energy products. Third, the interaction between trade-developed provinces (e.g., GD and JS) and the resource-based provinces (e.g., NM and HE) was the main pathway for government- and household-consumption-related carbon transfers.

However, there were also differences in the carbon transfer networks caused by government consumption and household consumption. First, the key nodes of both networks were Sector 16 and 20, but household consumption was more closely related to Sector 16, while government consumption was more influenced by Sector 20. Second, HA3 and HE10 were two of the key nodes in the household-consumption-related network, reflecting the high demand for food, tobacco, and metal products in household consumption. This revealed the essential difference between household consumption and government consumption: households directly consume energy and other products that cause carbon emissions, while the government indirectly generates carbon emissions through the provision of services. Third, the difference in betweenness centrality between the nodes of household consumption was smaller, and the spatial distribution of its networks was more balanced. In contrast, the betweenness centrality of the government consumption nodes differed significantly, with the top-ranked node, SD20 (284.50), far exceeding the bottom-ranked node, JS20 (62.01). This type of sector has an important impact on the rest of the network, and its carbon mitigation potential should be explored. In summary, policymakers need to focus on the carbon-driving influence of household consumption on the energy and service industries.

3. Capital formation

The social network of capital formation in China, which was the greatest contributor to ECEs and transfers, was mainly concentrated in Sectors 16 and 17, as shown in Figure 8d. Among the carbon transfer pathways induced by capital formation, JS16–JS17 ranked first with 71.36 Mt, followed by SD16–SD17 (69.35 Mt). Investment was one of the main drivers of China's industrial expansion over the past four decades, and real estate is one of the industries that most influenced by investment. The rapid expansion of real estate has led to a substantial increase in the utilization of construction materials. However, the production of construction materials (e.g., steel and cement) consumes considerable energy and generates serious carbon pollution, such as in HE10–HE17 (59.80 Mt), shown in Figure 8d.

From the perspective of network aggregation, it was found that the sectors of the inland provinces dominated most of the communities. For example, the orangish community (HE16, HE17, NM16, SX16, etc.) and the dark blue community (SN17, CQ17, SC17, XJ16, etc.) were mainly located in the inland and central region. This geographical distribution of communities reflected the characteristics of the real estate boom spreading from the coastal provinces to the inland provinces. Furthermore, JS16–JS17 were important carbon transfer pathways, but these two sectors were in different communities, which was similar to the case of NM16–NM17. This indicated that the construction industry not only absorbed carbon-intensive products from the provincial energy sector but also had strong carbon linkages with other provincial sectors. In summary, the government should limit the utilization of carbon-intensive materials in the construction sector and consider the embodied environmental pollution caused by inter-provincial trade.

5. Policy Implications

Based on the results of this study, some policy recommendations from various demand factor perspectives can be shared to promote China's comprehensive carbon mitigation strategy.

5.1. Export

In 2001, China successfully joined the World Trade Organization. Since then, the export trade has become one of the main driving factors of national economic development. The ECEs caused by export demand are transferred across inter-provincial trade and intra-provincial industrial chains, which creates some difficulties for the government to achieve its overall carbon reduction targets, as concluded in Sections 4.2 and 4.3.

Based on the study's findings, several recommendations are proposed. First, the export-oriented sectors represented by GD14 and ZJ14 should be prudent in purchasing equipment and expanding production lines, and they should actively promote low-carbon technologies such as intelligent integrated factories to mitigate carbon emissions. Second, they should raise the additional tariffs on the exports of metal and electronic equipment and promote the exports of products from low-carbon and environmentally friendly industries to reduce the pressure of export activities on the environment. Third, the export-induced carbon transfer network is highly concentrated and exhibits obvious small-world characteristics. Promoting low-carbon technologies and improving the energy utilization efficiency in key nodal sectors (e.g., GD14, HE10, and JS14) can widely influence the communities to which they belong, thus achieving holistic carbon mitigation. Fourth, in order to adhere to the dual-carbon macro target, the government needs to continue promoting the upgrading of low-value-added industries and breaking the bottleneck of strategic industries to fundamentally change the structure of export products and alleviate environmental pressure.

5.2. Household Consumption

The rapid economic development in China has brought about a thriving market economy, resulting in a rise in the demand for services and energy, triggering significant carbon emissions. In order to address this issue, several policy suggestions are presented below.

First, the structure of household consumption has the potential to be optimized by reducing the proportion of high-carbon products. To achieve this, the government should consider subsidizing clean products by offering consumption vouchers or environmental points, which would create a low-carbon consumer market. Additionally, an embodied carbon emission labeling system should be attempted, especially on the packaging of daily products, to promote public acceptance of environmentally friendly products. Furthermore, the establishment of a household carbon record system should be explored, which would reward residents with lower cumulative carbon emissions and encourage them to improve their consumption tendencies.

Second, for direct household energy consumption, metropolises should be encouraged to organize energy enterprise groups that cooperate with upstream industries to reduce carbon emissions. Metropolises, as both population centers and major contributors to household consumption, can negotiate and collaborate with upstream energy companies and form enterprise groups to require them to provide low-carbon products and phase out heavily polluting production plants. Additionally, energy enterprise groups can reduce the cost of new infrastructure (such as extra-high voltage grids and charging piles) through economies of scale, and they can enhance the share of green energy in the energy supply to reduce fossil energy pollution. For example, Beijing Gas Group has completed urban natural gas replacement and rural coal-to-gas conversion projects in the past two decades. Natural gas heating users now accounts for more than 97% of Beijing's heating, which greatly reduces the carbon emissions induced by the personal use of coal and gas. This type of energy group has promoted the transformation of Beijing's energy structure, which is worthy of reference for other provinces. In this way, carbon mitigation can be achieved for the entire energy supply chain, rather than for the city itself.

5.3. Government Consumption

In a broad sense, government consumption refers to the expenditure made by government departments to provide public services for the entire society. This study found that the carbon emissions embodied by government consumption were concentrated in the service industry, which heavily relies on products from the energy supply industry. Therefore, targeted carbon reduction actions led by local governments for emission reduction may be more feasible in metropolitan areas with strong administrative or public service functions, such as Beijing.

In order to achieve carbon mitigation goals, the ECEs generated by financial, real estate, scientific research, education, and other service industries related to government agencies need to be closely monitored, and clean government working models should be explored. Specifically, the government should: (i) Promote the construction of a government work network platform, establishing green data centers and government service outlets to achieve paperless offices. (ii) Enhance the energy efficiency of new buildings and implement the low-carbon retrofitting of existing buildings by increasing the installation area of rooftop photovoltaics, promoting heat pumps for heating, and improving the capacity of building energy management. (iii) Increase the utilization of pure electric and petrol–electric hybrid vehicles in business travel and increase the number of charging piles in public institutions. (iv) Invest in low-carbon technologies and purchase green products. Reducing energy consumption and carbon emissions in public institutions through administrative forces has great potential and should be considered by policymakers.

5.4. Capital Formation

After the 2008 financial crisis, investment gradually dominated China's economic development. However, the growth in investment demand has also led to exceeding expectations for growth in ECEs, which are primarily concentrated in the construction industry. Therefore, when developing carbon reduction policies, priority attention should be given to the construction industry because of its high demand for metal, non-metal, and energy products.

From a policy perspective, several recommendations can be made. First, the building sector should be guided to increase electrification levels and develop renewable energy buildings. Additionally, the upgrading of traditional buildings is critical, and the utilization of environmentally friendly building materials (e.g., plastic–metal composite pipes and bio-emulsion paints) should be considered. Second, upstream industries of the supply chain, such as the smelting and rolling of metals in Sector 10, should be strictly monitored. Investments in low-pollution raw materials should also be increased to advance the source control of carbon emissions. Third, the excessive development of infrastructure and factories should be controlled. A scientific assessment and planning system for the construction industry should be established to accomplish the goals of economic growth and environmental protection. The annual building increment should be properly planned, reduce the number of vacant buildings, and avoid the waste of materials and energy.

6. Conclusions

Investigating the mechanisms by which various demand factors influence the inter-provincial transfer of ECEs in China is crucial for identifying key nodal sectors and formulating targeted industrial policies. This study aimed to establish an I–O analysis framework combining HEM and CNA to evaluate the characteristics of China's inter-provincial transfer of ECEs induced by different demand factors. To achieve this, demand factors such as exports, household consumption, government consumption, and capital formation were selected, and their impacts on the inter-provincial transfers of ECEs were evaluated separately. In detail, (i) HEM was adopted to quantify the influence of various demand factors on the ECEs and their transfers in inter-provincial trading. (ii) CNA was employed to reveal the composition of sectoral clusters and locate the key sectors from the perspective of different demand factors to further explore the discrepancies in the spatial characteristics of carbon transfer networks caused by different demand factors. In general, the proposed framework has the potential to be applicable to other countries and pollutants to provide a scientific reference with which policymakers to develop rational and targeted carbon mitigation policies from multiple demand perspectives. The main conclusions are summarized as follows:

1. In 2017, the macro direction of China's carbon transfer was from north to south, from resource-rich provinces (e.g., Inner Mongolia and Shandong) to the industrially developed provinces (e.g., Guangdong and Zhejiang). Of these, the main contributors to carbon emissions were electric power, gas and water production and supply (2050.14 Mt), and the manufacture of metal products (639.17 Mt). This result is similar to the results of studies in regions with different economies and cultures [54,75,76]. Therefore, the government should encourage the adoption of clean production technologies in the energy and manufacturing industries to reduce their carbon intensity.
2. The carbon transfer caused by export factors was the most concentrated, and the main contributor was the manufacture of electrical machinery and electronic equipment in the southern provinces. For instance, Guangdong, the main recipient of carbon transfers due to export demand (197.92 Mt), received 77.95 Mt in GD14 (mainly from Inner Mongolia, Hebei, and Shanxi in the north), which accounted for 39.39% of the province. From a sector-specific perspective, the top-ranked export-related carbon transfer was HE10–GD14 (5.34 Mt), followed by NM16–GD14 (5.11 Mt). Seven of the top ten carbon transfers were from northern provinces (i.e., Hebei, Inner Mongolia, and Xinjiang) to southern provinces (i.e., Guangdong, Jiangsu, and Zhejiang), which coincides with Conclusion (1). In addition, the concentration of an export-related carbon transfer network was relatively

high, with the highest number of inefficient paths (47,607), a higher average path length (1.058), and a lower number of modular communities (13). The key export-side sectors represented by GD14 should be restricted from importing carbon-intensive products and encouraged to develop clean technologies.

3. The carbon transfer induced by household consumption factors was the most dispersed, and the factor obviously contributed to ECEs in sectors such as electric power, gas and water production and supply, and other services. The transfer network of ECEs induced by household consumption had the highest number of effective paths at 263,367, and it had 16 modular communities, which was higher than those of exports and capital formation. Therefore, in order to reduce greenhouse gas emissions, on the one hand, households should be incentivized to reduce the utilization of high-carbon and disposable products and to achieve low-carbon living goals by using green appliances, such as energy-efficient air conditioners, lighting, and refrigerators. On the other hand, the energy supply industry should be subsidized to develop cleaner production technologies and promote the recycling of renewable resources.
4. The total volume of inter-sectoral carbon transfers induced by government consumption was the lowest (206.25 Mt), accounting for 5.60% of all demand factors. However, the share of carbon-intensive products caused by government consumption was 39.34%, which was the highest of all demand factors. Among them, other services (including finance, real estate, research, healthcare, education, etc.) was the most important contributor. The government can reduce the ECEs in the provision of public services by promoting paperless offices and environmentally friendly official travel, advocating for the use of low-carbon packaging, purchasing green products, and promoting solar lighting and smart sensor lighting. It is also necessary to introduce green regulations for public buildings and their contractors, such as requiring the use of low-carbon materials for walls and windows and the installation of solar panels and rainwater recycling devices on the roofs of buildings.
5. Capital formation had the greatest impact on the carbon transfer in China, and its cumulative carbon transfer accounted for 55.98% of the total (2062.92 Mt). The construction sector in economically developed provinces was the most important driver of capital formation, such as in Zhejiang (116.15 Mt, 58.59%), Chongqing (116.97 Mt, 77.66%), and Guangdong (100.00 Mt, 61.38%). Policy restrictions and targeted subsidies should be applied to guide builders to use environmentally friendly materials (e.g., recyclable materials, thermal insulation materials, and eco-walls), install solar panels, and construct waste heat recovery systems to reduce carbon emissions throughout the building life cycle.

Although some important findings were obtained, this research still has the potential to be further explored in the future. First, methods such as Monte Carlo simulations can be used to assess some of the uncertainty in the information that may result from sectoral integration to eliminate discrepancies between different databases. Second, the present model can be applied to other countries and regions to analyze the characterization of their ECEs as influenced by different demand factors.

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