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Calculation and Intensity Analysis of Logistics Industry Embodied CO_2 Emissions in China

Zhaotong Sun[1], Yuanyuan Zhang[1*], Peidong Yu[1], Lanyi Zhang[1], Jie Pang[2]

[1] College of Transportation and Civil Engineering, Fujian Agriculture and Forestry University, 350002 Fuzhou, China
[2] College of Food Science, Fujian Agriculture and Forestry University, 350002 Fuzhou, China

[*] Correspondence: Yuanyuan Zhang (zhangyy@fafu.edu.cn)

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Abstract: China's logistics industry has been flourishing in recent years, with the high carbon emissions caused thereby receiving widespread attention. In this paper, the emissions and intensity of embodied carbon in the logistics industry in China are calculated for 2012, 2015 and 2017, using the multiregional input-output model and the changing trend. Additionally, influences of the intensity of embodied carbon emissions in the logistics industry across 30 provinces of China are assessed using the structural decomposition analysis method. The results show that from 2012 to 2017, the emissions of embodied carbon in the logistics industry from 30 provinces increased, while the intensity of embodied carbon emissions mainly decreased. The changes in the embodied carbon emissions intensity of the logistics industry are mainly affected by the direct carbon emission coefficient and added value coefficient. The intermediate input structure technology and the total scale of the final demand play a slight role in promoting the intensity of the embodied carbon emissions in the logistics industry. The direct carbon emission coefficient plays a major role in restraining provinces with negative intensity of embodied carbon emissions and promoting provinces with positive embodied carbon emissions intensity. The added value coefficient plays a major role in promoting the intensity of embodied carbon emissions. Finally, based on the analysis results, this paper presents suggestions for reducing the embodied carbon emissions in the logistics industry in 30 Chinese provinces, which include adjusting measures to local conditions, increasing the proportion of clean energy and clean technology in the logistics industry, increasing investment in green technology research and development, and improving the green technology innovation. Currently, researches on the implicit carbon emissions of the logistics industry focus mainly on the national, regional, and inter-provincial levels, with relatively few studies on the implicit carbon emissions of the logistics industry in each province. However, understanding the differences in the implicit carbon emissions of the logistics industry in each province and their influencing factors is crucial for identifying key emission reduction factors and developing carbon-neutral and carbon-reduction policies at the provincial level, which is the contribution that this paper makes.

Keywords: Multi-regional input-output analysis; Logistics industry; Embodied emissions; Structural decomposition analysis

1. Introduction

The logistics industry of China has boomed over the past few years, and its high carbon emissions have attracted widespread attention [1, 2]. According to the International Energy Agency, the carbon dioxide emissions from China's transportation industry increased by more than 3.5 times from 248 million tons (Mt) in 2000 to 901 Mt in 2019. The continuous increase in total carbon emissions puts tremendous pressure on the sustainable development of China's logistics industry.

In 2020, China announced the goal of reaching the carbon dioxide peak by 2030 and the vision of 2060 carbon neutrality [3]. The goal is to achieve peak CO_2 emissions by 2030 and carbon neutrality by 2060, and to promote international scientific and technological exchange and cooperation. Understanding the embodied CO_2 emissions

(ECEs) and their variation trend in the logistics industry in China's provinces can help the industry save energy and reduce emissions.

As economic globalization has been advancing significantly, researchers pay increasing attention to carbon leaking caused by the division of production and cross-border trade to the regional environment [4]. The traditional calculation method based on the energy consumption data cannot explain this phenomenon well. Therefore, some scholars proposed the carbon footprint concept, which is defined by Wiedmann and Minx as the direct or indirect carbon emissions generated over the entire life cycle of productions or services [5]. According to this definition, embodied carbon refers to the carbon emissions hidden behind economic activities in different regions to meet the consumption demand of a specific region and the resulting carbon emissions from production areas. Trade-embodied carbon significantly impacts the implementation of international climate governance policies, and the division of carbon emission-reduction responsibilities without the consideration of embodied carbon often causes controversy in the international community [6]. Comparing the difference between carbon emissions on the production and consumption sides allows reasonable consideration of the consumption side's carbon emissions, considering the embodied carbon flow [7]. Many studies are based on the national level, using environmentally-extended, multiregional input–output (EE-MRIO) models [8-10]. Comparing China's carbon emissions with the rest of the world can help China learn from others and build its experience. Regional variation and unbalanced development are China's basic national conditions [11]. Zhou et al. [12] estimated China's regional ECEs and their transfer through important regions and industries were examined from 2002 to 2012; Wei et al. [13] employed a network technique and the multiregional input–output model (MRIO) to measure the value-added and electricity-related carbon emissions included in China's interprovincial commerce from 2007 to 2012. Xu and Yang [14] measured the total carbon emissions of the logistics sector in Guangdong using the input-output approach from 2002 to 2017. Ma et al. [15] employed the structural decomposition analysis (SDA) method to break down the per-capita carbon emissions of Chinese citizens at the consumer level based on the MRIO method and the population consumption expenditure data in 2012, 2015 and 2017. Liu et al. [16] investigated the regional disparity changing trends of ECEs from urban households using the multiregional input–output model (MRIO) and SDA from 2002 to 2012 in China. The research on China's provincial carbon emission primarily focused on a single province's interprovincial mobility and carbon source mobility.

Regarding the decomposition analysis methods of factors influencing carbon emission intensity, existing studies mainly include SDA [17-19] and index decomposition analysis (INA) [20-22]. SDA is mainly used for cross-period research and decomposition of structural factors, which can compare and analyze the input–output tables of two different years; which has the characteristics of a dynamic input–output analysis method to some extent. Conversely, IDA is primarily used in current research. Hoekstra and Van den Bergh compared SDA and IDA, arguing that SDA can decompose the economic structure in more detail, and the input–output model incorporates indirect demand effects [23]. Hence, SDA is more suitable for this study. The current research on ECEs generally focuses on the national, interprovincial, and interregional levels, with little research on ECEs in the logistics industry. Therefore, the calculation and intensity analysis of the logistics industry ECEs in China's 30 provinces can better understand the differences in each province's ECEs concerning the logistics industry and the impact of its influencing factors to identify the key to reducing emission factors.

Therefore, this paper used China's provincial-level multiregional input–output (MRIO) table for 2012, 2015, and 2017 (42 sectors) to build the corresponding input–output model, calculate the ECEs of the logistics industry, and analyze the factors affecting the embodied CO_2 emissions intensity (ECEI) of the logistics industry. This ECEI is combined with SDA to provide a valuable reference to encourage the logistics industry to reach the goals of carbon peak and carbon neutrality as quickly as possible.

In the second section of this article, the analysis method and data source are introduced, mainly using the MIRO method with data from China Emission Accounts and Datasets (CEADs). In the third section, the implicit carbon emissions and intensity of the logistics industry in the 31 provinces of China are calculated, and the structural decomposition analysis method is used to judge the trend and influencing factors of the changes in implicit carbon emissions intensity. In the fourth section, a summary of the data from the third section is presented, and the conclusion is drawn that in 2012, 2015 and 2017, the implicit carbon emissions of the logistics industry in the 31 provinces of China showed an upward trend, while the implicit carbon emissions intensity showed a downward trend. The change in implicit carbon emissions intensity is mainly affected by the direct carbon emission coefficient and the value-added coefficient, while the intermediate input technology structure and the final demand total scale have a minimal impact on reducing the implicit carbon emissions intensity of the logistics industry.

2. Method and Data

2.1 Method

As for the data preprocessing, the MRIO method is adopted to compute the ECEs and ECEI of each province. Table 1 (Appendix) presents the study's three major industry categories [24].

The MRIO model can reflect the input and output relationship between regions and sectors. Furthermore, the environmental expansion input−output model can reflect the carbon emission flow between regions and sectors. It is applied to interregional carbon emission problems. It is supposed that the MRIO model contains *m* regions and *n* industries in the regional input-output table. It has the following row-direction connection.

$$Intermediate\ consumption + Final\ consumption + Export\ volume = Total\ output$$

The calculation formula is presented as below:

$$\sum_{s=1}^{m}\sum_{j=1}^{n} x_{ij}^{rs} + \sum_{s=1}^{m} y_i^{rs} = x_i^r (i = 1,2, \cdots, n) \tag{1}$$

where, $\sum_{s=1}^{m}\sum_{j=1}^{n} x_{ij}^{rs}$ represents the products' intermediate input used by department *j* in region *s* and department *i* in area *r*. y_i^{rs} reflects the production of final products of department *i* in region *r* or the ultimate consumption in area *s*. x_i^r column vectors show the overall output for sector *i* in the region *r*. The coefficient of direct consumption, often referred to as the technical effect, describes the relationship between producing one unit of one product and consuming another. The formula is as follows:

$$A_{ij}^{rs} = \frac{x_{ij}^{rs}}{x_j^s} (i, j = 1,2, \cdots, n) \tag{2}$$

Subsequently, substituting the above formula into formula (2) and its expression is a matrix:

$$\begin{bmatrix} A_{11} & \cdots & A_{1m} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mm} \end{bmatrix} \begin{bmatrix} X_1 \\ \vdots \\ X_m \end{bmatrix} + \begin{bmatrix} Y_1 \\ \vdots \\ Y_m \end{bmatrix} = \begin{bmatrix} X_1 \\ \vdots \\ X_m \end{bmatrix} \tag{3}$$

where, *A* represents the direct consumption coefficient matrix $mn \times mn$ and *Y* is the matrix of the final use matrix $mn \times 1$. Among them,

$$A_{rs} = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{n1} & \cdots & a_{nn} \end{bmatrix} \tag{4}$$

In the aforementioned formula, A_{rs} (s, r=1, 2, ⋯, m, $r \neq s$) represents the mutual demand matrix between production facilities in different geographies. When r=s, A_{ss} is the $n \times n$ order matrix, that is the matrix of the direct consumption in region s.

If $A \neq I$ and I-A is invertible, then:

$$\begin{bmatrix} X_1 \\ \ddots \\ X_m \end{bmatrix} = \left(I - \begin{bmatrix} A_{11} & \cdots & A_{1m} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mm} \end{bmatrix} \right)^{-1} \begin{bmatrix} Y_1 \\ \ddots \\ Y_m \end{bmatrix} = \begin{bmatrix} L_{11} & \cdots & L_{1m} \\ \vdots & \ddots & \vdots \\ L_{m1} & \cdots & L_{mm} \end{bmatrix} \begin{bmatrix} Y_1 \\ \ddots \\ Y_m \end{bmatrix} \tag{5}$$

where, *I* is the identity matrix, L^{rs} is a $n \times n$ leontief inverse, representing the total output used in region R for one unit of final demand in the region s.

Then, the carbon emission coefficient is defined as follows:

$$e_i^r = \frac{C_i^r}{X_i^r} \tag{6}$$

where, C_i^r, X_i^r, and e_i^r represent the total CO_2 emissions, total output, and direct CO_2 emissions per unit of output of sector *i* in region *r*. Carbon dioxide emissions calculated by CEAD are figured out in the input-output table when calculating carbon dioxide emissions by region and section. e_i^r is the CO_2 emission coefficient of the unit value of the output of the different sectors. The formula for the calculation of the ECEs in the region caused by the consumption is as follows:

$$CA^r = \hat{e}^r (I - A)^{-1} \hat{y}^r = C \times L \times F \tag{7}$$

There is the diagonal matrix, and $\hat{e}^r$ is the region's carbon emission coefficient. The full coefficient of emission of carbon dioxide, L, is the product of the direct carbon factor and the Leontief inverse, and the diagonal matrix $\hat{y}^r$ is the region *r*'s final demand.

Therefore, ECEs in each industry in each region are calculated. Similarly, the added value is calculated as follows:

$$VA^r = \hat{v}^r \times (I - A)^{-1} \times \hat{y}^r = \mathrm{V} \times L \times F \tag{8}$$

where, $\hat{v}^r$ represents the added value coefficient matrix obtained by diagonalizing v^r, which is the coefficient of value added of region r, and the formula is the value added divided by the total output of department i in region r.

Therefore, the ECEI VC^r of industry i in region r is constructed. The VC^r is as follows:

$$VC^r = \frac{CA^r}{VA^r} = \frac{C \times L \times F}{V \times L \times F} \tag{9}$$

The ECEI calculation can be decomposed into four effect factors: direct carbon emission coefficient effect (VC_C), added value coefficient effect (VC_V), structure of intermediate inputs effect (VC_L), and total final demand effect (VC_F). If the two levels are decomposed with 1 denoting the reporting period and 0 denoting the base period, the change factors can be decomposed as the following:

$$\begin{aligned} \Delta VC = VC^1 - VC^0 &= \frac{C^1 \times L^1 \times F^1}{V^1 \times L^1 \times F^1} - \frac{C^0 \times L^0 \times F^0}{V^0 \times L^0 \times F^0} \\ &= \{VC\_\mathrm{C}^{(0)}\} + \{VC\_\mathrm{V}^{(0)}\} + \{VC\_\mathrm{L}^{(0)}\} + \{VC\_\mathrm{F}^{(0)}\} \\ &= \{VC\_\mathrm{C}^{(1)}\} + \{VC\_\mathrm{V}^{(1)}\} + \{VC\_\mathrm{L}^{(1)}\} + \{VC\_\mathrm{F}^{(1)}\} \end{aligned} \tag{10}$$

If each variable is decomposed, the decomposition forms can be obtained. To solve the “non-unique” problem of SDA, the average value of two polar resolutions is used. The results are as follows:

$$VC\_C = \frac{1}{2}\{\mathrm{VC}\_C^{(1)} + \mathrm{VC}\_C^{(0)}\} \tag{11}$$

$$VC\_V = \frac{1}{2}\{\mathrm{VC}\_V^{(1)} + \mathrm{VC}\_V^{(0)}\} \tag{12}$$

$$VC\_L = \frac{1}{2}\{\mathrm{VC}\_L^{(1)} + \mathrm{VC}\_L^{(0)}\} \tag{13}$$

$$VC\_F = \frac{1}{2}\{\mathrm{VC}\_F^{(1)} + \mathrm{VC}\_F^{(0)}\} \tag{14}$$

2.2 Data

The data of 2012, 2015, and 2017 in China’s provincial-level MRIO table comes from CEADs [25]. The China Carbon Emissions Database CEADs (http://www.ceads.net) was developed by researchers from a number of Chinese and foreign research institutions to present the latest research results of China’s multi-scale energy, carbon emissions and socio-economic accounting inventories. It is updated every five years and the data for 2022 has not yet been updated, so data in 2012, 2015 and 2017 have been used for the analysis. Different industrial sectors’ direct carbon emission coefficients in each province are calculated based mainly on the CEADs [26-28]. The *Industrial Classification for National Economic Activities* does not explicitly classify the “logistics industry;” therefore, for the purposes of this paper, the transport, storage and communication sector, which accounts for more than 85% of the logistics industry, has been chosen as the representative sector.

3. Results

3.1 Analysis of the ECEs of the Logistics Industry in the 30 Provinces of China

In 2012, 2015 and 2017, most provinces’ ECEs showed an overall increasing trend, and the average annual growth rate was positive (Subgraph (a) of Figure 1). The changing trend of quantity can be divided into four types: gradual rise, fluctuation rise, gradual decline, and fluctuation decline. First, the ECEs of 18 provinces, including Xinjiang, Hunan, and Qinghai, trended upward. The ECEs in 2017 were significantly higher than those in 2012. Second, the ECEs of six provinces, including Jilin, Heilongjiang, and Shanghai, showed a fluctuating upward trend, with Jilin and Shanghai having a larger increase. Third, the ECEs of four provinces, including Tianjin, Hebei, Shandong, and Hainan, presented a fluctuating downward trend; and their ECEs in 2017 had a steadier current than in 2012. Finally, Inner Mongolia and Shaanxi trended gradually downward and were significantly reduced. Judging from the average annual growth rate, the ECEs had a smaller positive growth in 80% of provinces, while others were negative.

The share of ECEs in logistics shows a downward trend, with 80% of provinces rising from 2012 to 2015 and 60% between 2015 and 2017 (Subgraph (b) of Figure 1). Beijing, Shanghai, and Chongqing have relatively few primary and secondary industries and high per capita incomes. Tourism is one of the pillar industries in Hainan and Yunnan, while Guangdong has the highest services sectors in China, primarily based on wholesale and retail trade. Simultaneously, the proportion of ECEs in the logistics industry for service sectors presented a decreasing trend; with 17 provinces declining in 2012 and 2015, but 13 provinces increasing. Additionally, the proportion of ECEs in the logistics industry accounts for more than 50% of services sector in each province, except for Guizhou and Heilongjiang (Subgraph (c) of Figure 1). Jiangsu is the province with the largest proportion of ECEs in the logistics industry for services sectors from 2012 to 2017 because the province mainly focuses on industrial products, which account for more than 85%.

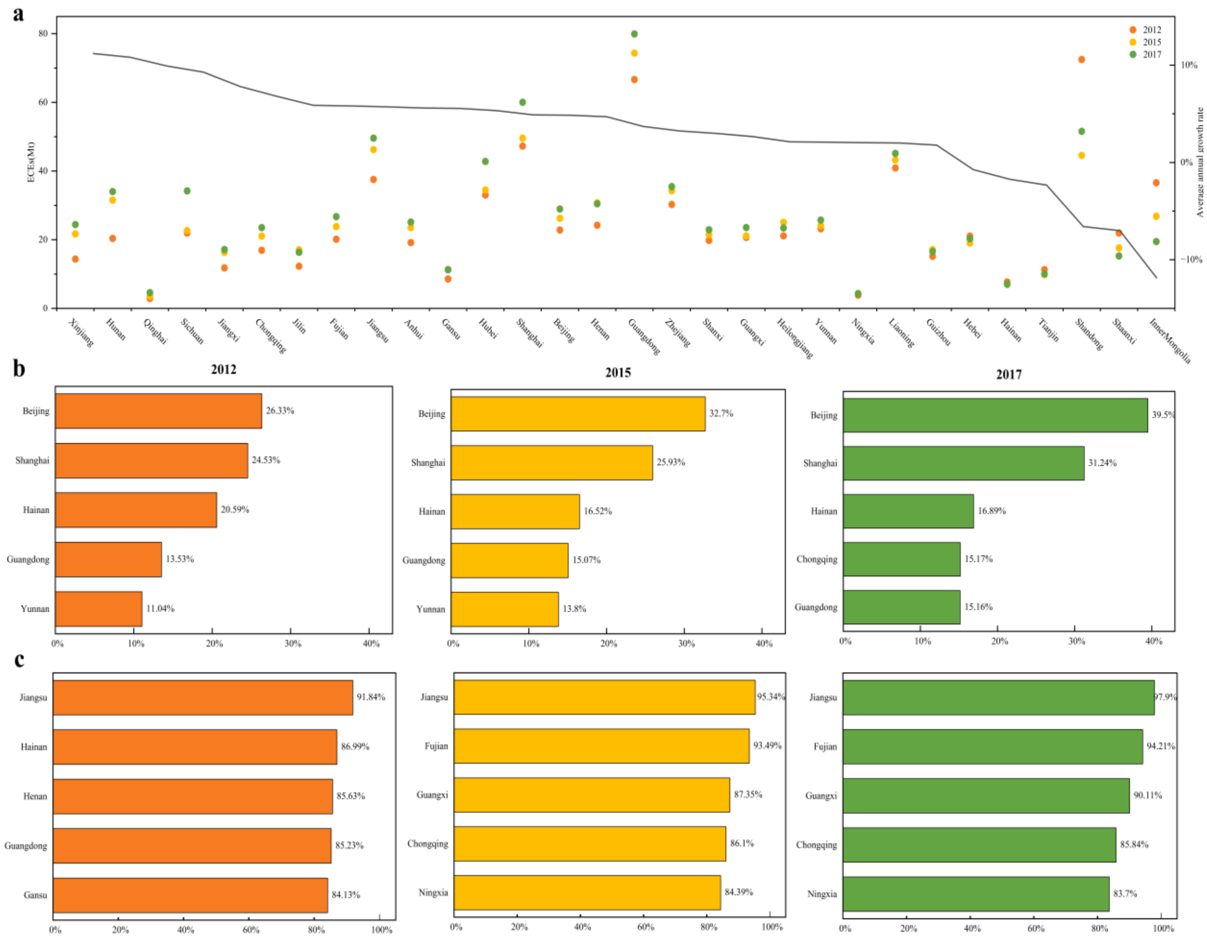

Figure 1. Quantity of logistics industry ECEs in China's 30 provinces: **a** Quantity and distribution of logistics industry ECEs in China's 30 provinces; **b** Top 5 logistics account for all industries of ECEs; **c** Top 5 logistics account for services sectors of ECEs

3.2 Analysis of ECEI in China's 30 Provincial Logistics Industry

The ECEI of the logistics industry presented from 2012 to 2017, a significant downward trend (Figure 2). Generally speaking, 26 provinces had negative changes in ECEI from 2012 to 2015, whereas 28 provinces had negative ECEI changes from 2015 and 2017.

From 2012 to 2017, the provinces with the top five ECEI changes in logistics were in less developed areas, except for Shanghai and Fujian. In comparison, from 2012 to 2017, the provinces with the bottom five ECEI changes in logistics were in developed areas except for Hebei. Yunnan has shown the highest ECEI from 2012 to 2017, and coal primarily dominates its energy structure. Fujian has a higher ECEI owing to the high energy consumption intensity from 2012 to 2015, while the considerable decline is mainly due to the implementation of the 13th Five-Year Plan; from 2015 to 2017, the plan will reduce the share of coal in energy and increase the share of clean energy in the energy structure. Hebei has the lowest ECEI among the provinces because its logistics and technical efficiency are high.

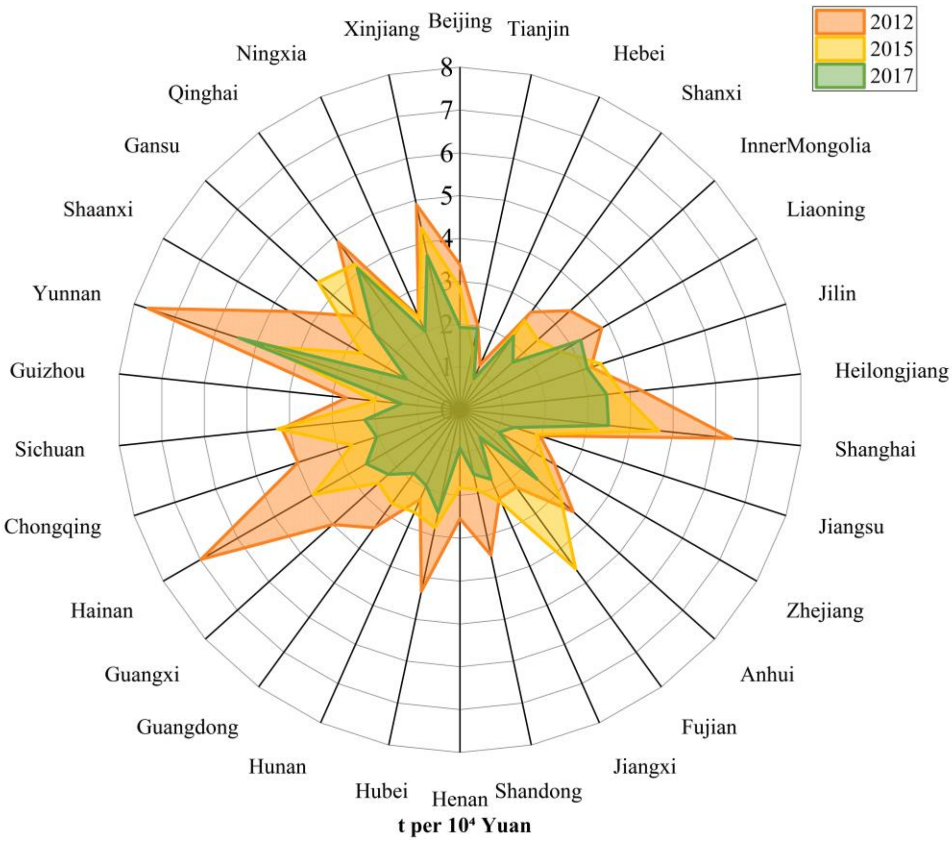

Figure 2. ECEI in China's 30 provinces for the logistics industry

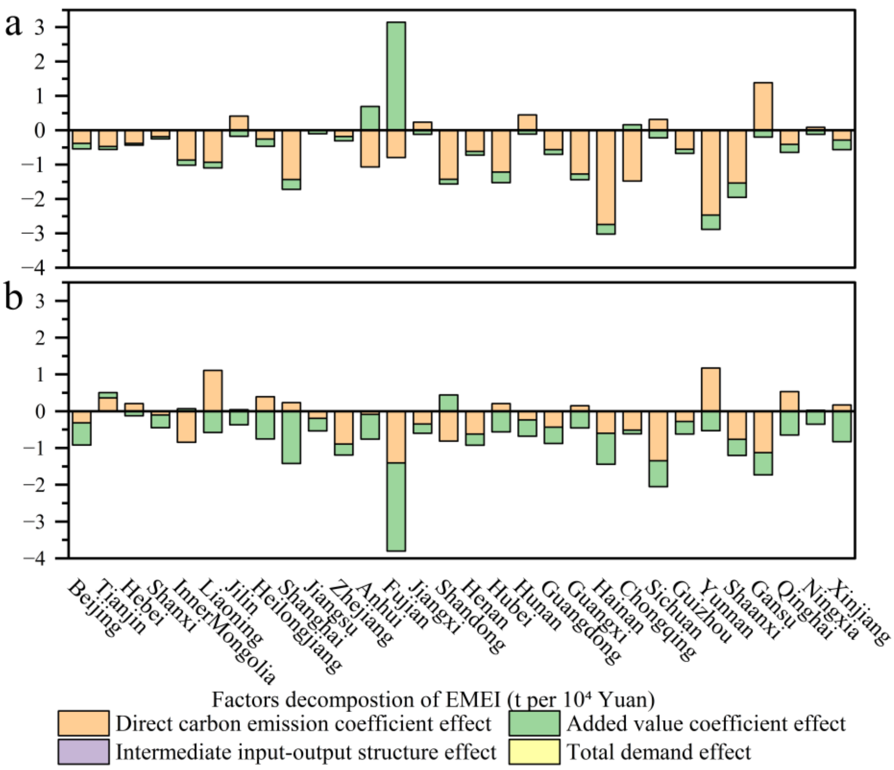

Figure 3. Factors decomposition of ECEI in China's 30 provinces from 2012 to 2017: **a** Factors decomposition of ECEI in China's 30 provinces from 2012 to 2015; **b** Factors decomposition of ECEI in China's 30 provinces from 2015 to 2017

Note: The inter input structure effect and total demand effect are too small, so they are omitted.

The influencing factors of ECEI in the logistics industry in 30 Chinese provinces have some differences in the effect of ECEI, which are primarily embodied through the effects of direct carbon emission coefficient and added value coefficient (Figure 3). During the reporting period, the effect of the direct carbon emission coefficient helped reduce ECEI in the logistics industry from 2012 to 2015, while the added value coefficient effect mainly impacted ECEI's reduction from 2015 to 2017.

During the reporting period, the direct carbon emission coefficient is positive in 6 provinces and negative in 24 from 2012 to 2015. Specifically, Gansu has the largest effect value of 1.387 tons per 10^4 Chinese yuan (CNY), followed by Hunan, Jilin, Sichuan, and Jiangxi (0.445, 0.413, 0.315, and 0.234, respectively). In comparison, the direct carbon emission coefficient is positive in 12 provinces and negative in 18 provinces from 2015 to 2017. Yunnan has the largest effect value of 1.171 tons per 10^4 CNY, followed by Liaoning, Qinghai, Heilongjiang, and Tianjin (1.108, 0.532, 0.393, and 0.363, respectively). The direct effect of the carbon emission coefficient inhabits ECEs mainly due to effective implementation of policies to save energy and reduce emissions. Furthermore, the research and development of energy-saving and emission-reduction technologies have actively promoted the progress of energy-saving technologies in China, contributing to a substantial reduction in carbon emission intensity.

Moreover, there are consistently 4 provinces with positive added value coefficient effect and 26 with negative effect from 2012 to 2017. Fujian and Shandong had the largest changes from 2012 to 2015 and 2015 to 2017, with effect values of 3.144 and 0.444 t per 10^4 CNY, respectively. Simultaneously, Shaanxi and Fujian were the smallest in 2012−2015 and 2015−2017, with effect values of −0.416 and −2.401 tons per 10^4 CNY, respectively. The added value coefficient inhabits ECEs because the supply-side structural reform has been identified as the main development line of China's 13th Five-Year Plan period, which can promote the industry to move toward the mid-to-high end on both the supply side and the demand side.

4. Conclusions and Implications

Based on the MRIO table of the 30 provinces in China from 2012 to 2017, this paper is to calculate the ECEs and intensity of the logistics industry, simultaneously combining the SDA to analyze the impact factors of the ECEs in the logistics industry. The conclusions can serve as a reference for the energy saving and emission reduction policies of the logistics industry in China's provinces, autonomous regions and municipalities, and provide valuable suggestions for the early realization of reaching the carbon peak and carbon neutrality targets for the logistics industry.

First, from 2012 to 2017, the ECEs of China's logistics industry primarily increased, while the ECEI of the logistics industry presented a significant downward trend. Therefore, adaptation measures should be adapted to local conditions in each province. The ECEs and intensity of the logistics industry in each province differ; thus, it is necessary to implement emission-reduction policies for the green and healthy development of the industry. Such policies should consider the regional economic development and the goals of national carbon peak and carbon neutrality according to their actual conditions to achieve the overall optimal carbon emission-reduction effect.

Second, in 30 Chinese provinces, the direct carbon emission coefficient and added value coefficient primarily impact the change of ECEI in the logistics industry. Conversely, the intermediate input structure and total demand play a small role in reducing the ECEI of the logistics industry. The effect of the direct carbon emission coefficient contributed to the reduction of ECEI in the logistics industry from 2012 to 2015, whereas the added value coefficient effect mainly affected the reduction of ECEI from 2015 to 2017. Therefore, increasing the proportion of clean energy and clean technology in the logistics industry is necessary. The reduction of the direction emission coefficient of the logistics industry is mainly due to favorable implementation of measures to save energy and reduce emissions and the widespread use of related technologies. In the future, the logistics industry should gradually replace the energy structure dominated by traditional fossil fuels, increase the production of primary power (hydroelectric power, wind power, photovoltaic power, and nuclear power) in the energy structure, and achieve carbon peak and carbon neutral goals. Additionally, increasing investment in green technology research and improving the level of related innovations is essential. The extensive application of green technology in the logistics industry is key to reduce ECEs and their intensity with the effects of the added value coefficient and the intermediate input-output structure. The logistics industry should invest more in researching and developing green technologies, introduce high-level technical talents, break down technical barriers, and improve green technology innovation. Furthermore, the industry should increase investment in green technology research and development and the effect of intermediate input technology structure on the increase of ECEI.

This study estimated the implied carbon emissions of the logistics industry in 31 provinces of China using data from 2012, 2015, and 2017. The data after 2017 is unclear, especially since the central government proposed the carbon neutrality and carbon peak targets after 2020. The differences in carbon emissions among provinces are not yet known, but the data will be updated in the future to provide more accurate references for achieving the dual carbon goals and formulating carbon reduction policies by the government.

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Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Appendix

Table 1. Reclassification of 42 sectors in the input-output table

NO.	Three major industry	Input-output table department
1	The primary industry	Agriculture, Forestry, Animal Husbandry, and Fishery
2	Manufacturing industries	Mining and washing of coal, Extraction of petroleum and natural gas, Ming and processing of metal ores, Mining and processing of nonmetal and other ores, Food and tobacco processing, Textile industry; Manufacture of leather, fur, feather, and related products, Processing of timber and furniture, Manufacture of paper, printing, and articles for culture, education and sport activity, Processing of petroleum, coking, processing of nuclear fuel, Manufacture of chemical products, Manuf. of non -metallic mineral products, Smelting, and processing of metals, Manufacture of general purpose machinery, Manufacture of transport equipment, Manufacture of communication equipment, computers and other electronic equipment, Manufacture of measuring instruments, Other manufacturing, Comprehensive use of waste resources, Repair of metal products, machinery and equipment, Production and distribution of Gas, Production and distribution of tap water, Construction
3	Services sectors	Wholesale and retail trades, Transport, storage, and postal services, Accommodation and catering, Information transfer, software and information technology services, Finance, Real estate, Leasing and commercial services, Scientific research and polytechnic services, Administration of water, environment, and public facilities, Resident, repair and other services, Education, Health care and social work, Culture, sports, and entertainment, Public administration, social insurance, and social organizations