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Logistics Efficiency under Carbon Constraints Based on a Super SBM Model with Undesirable Output: Empirical Evidence from China’s Logistics Industry

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Abstract: As world resources and environmental constraints have increased, environmental cost has become a concern that affects the sustainable development of the logistics industry in various countries. Carbon emissions are an important part of any environmental cost assessment. How to scientifically and rationally evaluate the green GDP impact and regional efficiency in the logistics industry, especially when under carbon emission constraints, is of great significance to the realization of green and sustainable development. This study evaluated the logistics efficiency of 30 provinces in China from 2003 to 2016 by constructing a super SBM (Slack Based Model) model with undesirable output to explore provincial efficiency and its regional differences. The input–output ratio of the regional logistics industry was optimized through the calculation of the frontier slack variables. The research results showed that, first, it was more reasonable to adjust efficiency under carbon constraints, and it was consistent with the actual performance of the logistics industry. Second, technological progress and deeper capital investments promoted the development of the logistics industry, but technological barriers and low-scale efficiency between regions often limited technological efficiency. Therefore, decision-makers in the logistics industry should reconsider the challenges presented in each reason, encourage industrial technological innovation between regions, and especially promote energy-saving and emission-reduction technologies, so as to maintain the sustainable growth of the logistics industry.

Keywords: logistics efficiency; technological efficiency; scale efficiency; undesirable output; super SBM model

1. Introduction

Logistics are an important way to promote the effective allocation of productive forces and the means of production across regions, and efficient logistics capabilities are an accelerator for regional economic development [1]. With rapid advancements in e-commerce, the logistics industry has also advanced significantly in recent years. Its development has coordinated the advancements in related industries and injected new vitality into economic development [2–4]. The logistics industry is a composite service industry integrating transportation, warehousing, freight forwarding, information, and other industries. The development level of the logistics industry has become one of the key indicators for the comprehensive strength of a country or region [5]. However, the logistics industry is a high-carbon emission industry, which is subject to resource and environmental constraints, and energy consumption and environmental pollution...
are relatively serious [6]. Carbon restriction has helped to improve logistics efficiency and achieve sustainable improvements [7–9] and efficiency in the industry [10–14], and countries have been researching logistics technology and innovation.

This paper provides an overview of the relevant literature on the challenges and technological advancements of sustainable logistics, and the role of logistics systems in addressing these challenges [13,14]. Kechagias et al. suggested that the use of systems thinking and system dynamics could identify and optimize key factors, achieve effective and efficient interconnection operations, and significantly improve the process [15]. Hahn used the theoretical perspective of supply chain innovation (SCI) to study the impact of Industry 4.0 on supply chain management. The SCI-supported i4.0 has been reflected in three aspects: process, technology, and business architecture. The tenets of i4.0 has enabled SCIs to extend the focus on process productivity improvements to scalability and flexibility [16]. Gayialis et al. analyzed the development of information systems to support the efficient delivery of goods within urban areas. The system utilizes a set of OR algorithms enabled by information technology to efficiently support logistics operations [17]. Gayialis proposed a way to create a blockchain traceability and labeling platform. The platform uses several advanced technologies such as blockchain, anti-counterfeiting labels, smart contracts, and sensors to provide effective traceability for all stages of the product supply chain [18]. All of these show that, in order to improve the sustainable development capability of the logistics industry, that is, to improve the efficiency of green logistics, we must start from the aspects of people, systems, processes, and technologies. The logistics industry may achieve green, low-carbon, and sustainable development.

At this stage, China’s logistics industry has incurred a relatively large sum while promoting economic development. The logistics industry is characterized by large scale and high cost. The logistics cost of the whole society in China continued to grow, with a year-on-year increase of 7.3% in 2019 to CNY 14.6 trillion [19]. On the other hand, the environmental cost in the development of the logistics industry is also increasing, and energy efficiency and environmental pollution have become the limiting factors for the sustainable development of the industry. In 2011, the carbon emission of China’s logistics industry was 1.6299 tons, which was 3.8 times that of 2000, and the average growth rate was as high as 12.9% [20]. With the development plan for green logistics and its efficiency, China’s logistics industry has entered a transition period of high quality, low energy consumption, and low pollution from extensive development. Therefore, when studying the current sustainable development of the logistics industry, it is very important to consider the environmental costs and calculate the green production efficiency. In addition, China, as a large country, has different levels of economic development in different regions; therefore, the green production efficiency of the logistics industry may also vary. Therefore, it may be more meaningful to study this issue at a regional level [21]. After considering the environmental costs, what kind of regional characteristics affect the efficiency, and what are the causes of any differences? Answering this question may provide support for differentiated policy recommendations for different regions.

The main contributions of this study were that we established an analytical framework for the measurement and decomposition of logistics efficiency under carbon constraints and explored the mechanism of regional differences impacting efficiency, environmental improvements, and optimization. For our empirical analysis, we used the following: (1) a super SBM model for measuring logistics efficiency under carbon constraints, which considered undesirable outputs; (2) the MAX-DEA (Max Data Envelopment Analysis) method to measure and decompose the logistics efficiency of 30 provinces in China into pure technological efficiency and scale efficiency; (3) frontier relaxation variables to determine the causes and influencing factors, to optimize the input–output ratio of regional logistics industry, and to analyze the relationships among inter-regional scale efficiency, technological barriers, capital deepening, and logistics efficiency.
2. Literature Review

The existing literature has suggested that the differences found in logistics industry efficiency is a result of micro- and macro-level aspects. The micro-impact stems mainly from the company itself, the users, and the environmental constraints of the enterprise. Firstly, the cost, the quality, the time, and the logistics system will affect the logistics efficiency of enterprises [4]. Secondly, the trust of users and the timeliness of communication also impact the efficiency of logistics enterprises, while satisfaction, opportunity, and reputation indirectly affect the production efficiency of logistics enterprises and influence trust [2]. In addition, the long-term sustainable green investment of enterprises will affect energy and governance costs [3]. From a macro-perspective, the logistics hub and enterprise operation costs are the internal influencing factors of regional logistics efficiency [5], while the local resource constraints and the government’s sustainable development policy are the external factors affecting efficiency. For example, Gayiali et al. found that the implementation of an intelligent logistics distribution policy could improve the efficiency of the logistics industry and reduce carbon emissions, but whether to promote such a policy was related to the local economy [18].

There have been many studies on sustainable logistics that have focused on sustainable logistics network design, supply chain innovation, and new logistics concepts. Neto et al. designed and formulated a framework for sustainable logistics, using multi-objective planning to design sustainable networks to minimize costs and environmental impacts [22]. Lee et al. noticed that with increasingly stringent environmental and social requirements, the design of sustainable logistics networks has received more and more attention. They proposed a stochastic programming approach to analyze the design of sustainable logistics networks under uncertainty [23]. Wei suggested that the logistics network was the decisive factor for the success of an integrated supply chain. Combining a reverse logistics network with a forward logistics network could achieve a socially, economically, and environmentally sustainable logistics network [24]. Digiesi et al. argued that social and environmental costs should be considered in a sustainable manufacturing framework. They proposed an inventory model to support decisions on transport mode selection and sustainable order quantities, which would minimize the logistical and environmental costs [25]. Zhi designed a sustainable supply chain model that used rental services in a loop [26]. Knaak et al. suggested new logistics concepts that could reduce costs, distances, and emissions, and could improve economic and ecological issues by increasing the application of cargo bundling and using bicycle couriers [27].

Most research uses SFA (Stochastic Frontier Model) and DEA to perform the quantitative analysis of logistics efficiency. Among them, the DEA method is an efficiency evaluation method designed for multiple inputs, outputs, and decision-making units, whereas the DEA method has been widely used to measure logistics efficiency and performance [28–32]. It has also been used to calculate the efficiency of achieving sustainable operation performance at the national level, which could indicate sources of low efficiency and promote performance improvements in logistics [33–35]. Fare et al. used the CCR-DEA model to conclude that green logistics required less energy input (e.g., oil) to increase economic output [36]. In this case, when considering undesirable outputs such as carbon emissions, the traditional DEA model was not suitable for evaluating low-carbon economic efficiency [37]. With the increasingly prominent problem of environmental pollution, many researchers have included the undesirable outputs, such as carbon emissions, into the framework of efficiency measurement and improved the traditional DEA method. Tone first combined the slack-based measure (SBM) with the DEA model to treat undesirable outputs and then considered the slackness of the inputs and outputs caused by radial and angle selection and directly solved the problem of excessive inputs and insufficient outputs in efficiency measurements [38,39]. SBM-DEA is a cutting-edge research method, which has been widely used for various applications in the field of efficiency research. For example, China’s cultivated land-use efficiency considered carbon emissions and sustainable efficiency of regional transportation under environmental pollution conditions [40,41].
Researchers have reached a consensus regarding improving the efficiency of logistics while reducing energy consumption and environmental pollution, but only a few have used the SBM-DEA method to study logistics efficiency under carbon constraints. Zhang et al. studied logistics efficiency under carbon constraints at the national level [42]. They used SBM-DEA to construct a low-carbon logistics performance index ranking 104 countries and found that developed countries had better performance; China, as the second largest carbon emitter, was used to verify the effectiveness of their model. Yu et al. studied the ecological impact of logistics efficiency with a “super” SBM-DEA combined with the global Malmquist index at the regional level [43]. They evaluated the ecological logistics efficiency of 11 provinces and cities in the Yangtze river economic belt (YREB) from 2004 to 2016. To date, no research has applied the super SBM-DEA model to study logistics efficiency under carbon constraints in all the administrative regions of China.

This study employed the super SBM-DEA model to evaluate the green output efficiency of logistics in China. Based on panel data from 30 administrative regions in China (excluding Xi Zang, Hong Kong, Macao, and Taiwan) from 2003 to 2016, this study examined the regional logistics efficiency in China under carbon constraints and analyzed its time evolution and spatial distribution. By decomposing and measuring logistics efficiency, we identified the causes of regional differences and further analyzed the slack variables and optimization factors for the production in each region. Finally, we classified and analyzed efficiency improvements and challenges in a low-carbon economy. In this study, the output efficiency under carbon emission constraints was divided into pure technological efficiency and scale efficiency, focusing on energy utilization and the economics of carbon emission, and we provided targeted suggestions for improving logistics efficiency under resource constraints.

3. Methodology

Data envelopment analysis (DEA) is a non-parametric mathematical programming method that has been used to evaluate the relative effectiveness of DMUs, namely the CCR-DEA model [44]. The DEA model has been widely used in the measurement of logistics efficiency, as this method can deal with multiple input and output data from the economy and environment and does not need the functional form assumption between input and output, so it can avoid the subjectivity of artificially set parameters. In the actual operation, when putting human, material, and energy parameters into the logistics, it has produced the expected economic efficiency, but it has also considered the degree of impact on the environment, such as carbon emissions. Ideal effective logistics efficiency should consider a certain input to achieve the desired economic output while reducing the undesirable output, such as carbon emissions. Therefore, the traditional DEA model was not suitable for efficiency evaluation when considering carbon emission.

The slack-based measure (SBM) model was first proposed by Tone [38]. On the basis of the DEA model, the slack variable was entered into the objective function, and it was further extended to handle the undesirable outputs since it belonged to the non-radial, non-angular DEA model. It effectively solved the problem of excess inputs and insufficient outputs between decision-making units through redundant measurements, and the calculated efficiency value was between 0 and 1. In practical applications, in order to sort efficient decision-making units and optimize decision-making and management, researchers have continued to add more constraints to these basic research models, and therefore, a super-efficient model (super SBM model) was created. The super-efficient DEA model combines super-efficiency and the SBM model. As compared to the general radial DEA model (radial BCC/CCR), relaxation was also considered, which was a better super-efficiency model. Based on existing research, this study constructed a super-SBM model that considered undesired outputs to evaluate efficient DMUs.

This study supposed that the efficiency of n DMUs was measured, and each DMU was composed of input, expected output, and undesirable output. The input, expected output, and undesirable output matrices were represented by $X$, $Y^e$, and $Y^{ue}$, respectively.
When \( \beta \) were not considered in Tone’s super SBM [39]. Therefore, in order to evaluate the efficiency variables have the same meanings as in Equation (1).

In later research, Tone proposed the super-SBM model. However, the undesirable outputs development efficiency of multiple regions was at peak DEA efficiency (multiple to sort and evaluate the decision-making unit. There were also situations where the logistics output may have multiple situations that are simultaneously effective, so it is not convenient it is necessary to adjust the input and output. At this point, the SBM model of undesirable is necessary to adjust the input and output. At this point, the SBM model of undesirable.

Based on Tone’s SBM model [38], the SBM model handling undesirable outputs can be measured as follows:

\[
\min \beta = \frac{1 - \frac{1}{m} \sum_{i=1}^{m} \frac{\omega_i}{x_{ik}}}{1 + \frac{1}{r_1 + r_2} \left( \sum_{s=1}^{r_1} \frac{\omega_s}{y_{sk}^q} + \sum_{q=1}^{r_2} \frac{\omega_{ue_s}}{y_{qk}^{ue}} \right)}
\]

s.t. \( x_{ik} = \sum_{j=1}^{n} x_{ij} \alpha_j + \omega_{i}^{\prime}, i = 1, \ldots, m \)

\( y_{sk}^q = \sum_{s=1}^{r_1} y_{s}^{q} \alpha_j + \omega_{qs}^e, s = 1, \ldots, r_1 \)

\( y_{qk}^{ue} = \sum_{q=1}^{r_2} y_{q}^{ue} \alpha_j + \omega_{ue_q}^e, q = 1, \ldots, r_2 \)

where \( \lambda \) is the weight vector, \( \lambda_j > 0, j = 1, \ldots, n, \omega_{i}^{\prime} > 0, i = 1, \ldots, m, \omega_{qs}^e > 0, s = 1, \ldots, r_1, \omega_{ue_q}^e > 0, q = 1, \ldots, r_2 \), and \( \beta \) is strictly diminishing on \( \omega_{i}^{\prime}, \omega_{qs}^e, \omega_{ue_q}^e \) and has values in the range \([0, 1]\). DMU\(_k\) is SBM-efficient if, and only if, \( \beta = 1 \); that is, \( \omega_{i}^{\prime} = \omega_{qs}^e = \omega_{ue_q}^e = 0 \). When \( \beta < 1 \), it means that DMU\(_k\) is inefficient. There is redundancy in the input, and it is necessary to adjust the input and output. At this point, the SBM model of undesirable may have multiple situations that are simultaneously effective, so it is not convenient to sort and evaluate the decision-making unit. There were also situations where the logistics development efficiency of multiple regions was at peak DEA efficiency (multiple \( \beta \) equals 1).

In later research, Tone proposed the super-SBM model. However, the undesirable outputs were not considered in Tone’s super SBM [39]. Therefore, in order to evaluate the efficiency of the decision-making units accurately, the proposed super SBM model was optimized based on a weak dispositional assumption. Assuming that DMU\(_k\) is SBM-efficient, the corresponding super SBM model with undesirable outputs is given as follows:

\[
\beta' = \frac{1 + \frac{1}{m} \sum_{i=1}^{m} \frac{\omega_{i}^{\prime}}{x_{ik}}}{1 - \frac{1}{r_1 + r_2} \left( \sum_{s=1}^{r_1} \frac{\omega_s^e}{y_{sk}^q} + \sum_{q=1}^{r_2} \frac{\omega_{ue_s}}{y_{qk}^{ue}} \right)}
\]

s.t. \( x_{ik} \geq \sum_{j=1, j \neq k}^{n} x_{ij} \lambda_j - \omega_{i}^{\prime}, i = 1, \ldots, m \)

\( y_{sk}^q \leq \sum_{j=1, j \neq k}^{n} y_{s}^{q} \lambda_j + y_{s}^{q}, s = 1, \ldots, r_1 \)

\( y_{qk}^{ue} \geq \sum_{j=1, j \neq k}^{n} y_{q}^{ue} \lambda_j + y_{q}^{ue}, q = 1, \ldots, r_2 \)

where the objective function is \( \beta' \), whose value can be more than 1, and all the other variables have the same meanings as in Equation (1).
According to Equations (1) and (2), the annual logistics efficiency in various regions of China under carbon constraints is calculated, represented by LIE, and it can be expressed as:

$$LIE = \begin{cases} \beta, & 0 < \beta < 1 \\ \beta', & \beta > 0 \end{cases}$$  

(3)

As compared to other DEA models, this super SBM model, while considering undesirable outputs, solved three problems that have existed in previous efficiency evaluations [45]: first, the undesirable output factors were included in the analysis category; second, the relaxation of input-output variables was effectively solved; third, the problem of multiple decision-making units appearing simultaneously at the forefront and unable to be effectively ranked was solved. Therefore, the model (2) could measure and evaluate the efficiency of regional logistics comprehensively [46].

4. Variable Selection, Data Resources and Preliminary Analysis

4.1. Variable Selection and Data Resources

At present, previous designs for the measurement of logistics efficiency have been based on KLEMS method, that is, capital, labor, energy, materials, and S-purchased services were used as input with industrial GDP as output to measure the efficiency of logistics. The rationality of index selection directly affects the efficiency evaluation of the decision-making unit. Therefore, using the principles of data availability, comprehensive analysis, and index simplicity, we selected capital, labor, and energy as input indices, added the value of logistics as expected output, and included carbon dioxide emission as undesirable output. Thirty provinces and cities in China were selected as the research objects. Tibet was not included in the research objects due to the lack of relevant energy data. The sample range was between 2003 and 2016, a total of 14 years of data. The statistical data of added value, labor input, fixed asset investment, energy input, and carbon emission of regional logistics as well as the original data of added value, labor, and fixed asset inputs were sourced from the statistical yearbooks of the corresponding years, and the data of energy input and undesirable output were sourced from China’s energy statistical yearbooks of the corresponding years. Missing data were replaced using relevant data in China’s urban statistical yearbooks, tertiary industry statistical yearbooks, environmental statistical yearbooks, logistics data platform websites, and regional logistics statistics bulletins.

Since modern logistics is a composite service industry integrating transportation, storage, postal, and telecommunications industries, “logistics” were not listed in the classification of global industrial systems, even in China. According to China’s tertiary industry statistical yearbooks 2000–2017, in 2003–2016, the added value of transportation, storage, and postal industries accounted for more than 80%. Therefore, this study selected the relevant data from the transportation, storage, and postal industries to approximate their development level in logistics. In order to enhance their comparability, the data were described as follows.

First, the employment personnel reflected the total labor force or at least those that participated in the actual logistics production. The labor input was expressed by the average number of annual employment labor personnel in logistics; second, the capital input was expressed using fixed assets. According to the perpetual inventory method, the net value of fixed assets at the end of the year should be converted in the logistics:

$$C_t = C_{t_0} + \sum_{t_{t+1}} \frac{\Delta C_i}{p_i(t)}$$  

(4)

where $C_{t_0}$ is the annual average balance of net value of fixed assets in 2003, and $\Delta C_i$ is the increased net value of fixed assets in year $t$; these are expressed by the difference between the net value of fixed assets in the adjacent two years. The price index $p_i(t)$ of fixed asset investment in various industries was converted into 2003’s constant price. Third, the energy input of logistics was expressed by six kinds of energy consumption (i.e., raw coal, gasoline, kerosene, diesel oil, fuel oil, and natural gas) that were converted into standard coal in each
region. Fourth, the added value of logistics in each region was equal to the expected output, and 2003 was the base period. It was the conversion of comparable prices by GDP deflator method. Fifth, the undesirable output was expressed by the carbon dioxide emission of the logistics in each region, and the carbon emission was calculated based on the six main energy consumption in each region. The calculation formula is:

$$Ca = \sum_{i=1}^{6} Ca_i \times P_i$$

(5)

where $P_i$ stands for energy consumption converted to standard coal of the energy type $i$, and $Ca_i$ stands for the carbon emission factor corresponding to energy source $i$.

4.2. Statistical Description and Analysis of Efficiency Evaluation Indices

The descriptive statistical results of sample data of input–output indicators of logistics in China’s 30 regions are shown in Table 1. During the 14-year time period, the average labor employment in logistics was 224,100, while the average capital input was CNY 73.542 billion, and the average energy input was 526,200 tons of standard coal. In terms of output, the expected annual output was CNY 69.318 billion, while the industry’s annual carbon dioxide emissions were 2.8435 million tons.

| Index name         | Labor Force | Energy | Capital | Added value | CO2 emissions |
|--------------------|-------------|--------|---------|-------------|---------------|
| Variable           | L           | E      | C       | G           | Ca            |
| Unit               | 10,000      | 10,000 tons of standard coal | Billion yuan | Billion yuan | 10,000 tons   |
| Minimum            | 0.6         | 0.15   | 25.81   | 11.1        | 5.8           |
| Maximum            | 85.4        | 732    | 3738    | 3209.72     | 1553.8        |
| Mean               | 22.41       | 52.62  | 735.42  | 693.18      | 284.35        |
| Standard deviation | 14.25       | 104.58 | 658.97  | 608.08      | 234.59        |
| Centermost element | 20.45       | 21.27  | 536.68  | 536.59      | 209.2         |

To further understand the correlation between the efficiency evaluation indices of the logistics and conducted the correlation analysis, the data in Table 2 show that all the correlation coefficients between input and output were significantly positive, which proved the “isotonicity” of input and output in the model (Mostafa, 2009). There was a slight degree of fungibility between labor and energy inputs, and other indicators were positive correlations. Therefore, it further confirmed that these data could be used to evaluate the low-carbon economic efficiency of regional logistics.

|          | L  | E     | C     | G     | Ca  |
|----------|----|-------|-------|-------|-----|
| L        | 1  |       |       |       |     |
| E        | -0.0170 | 1     |       |       |     |
| C        | 0.5399 | 0.0549 | 1     |       |     |
| G        | 0.7224 | 0.0186 | 0.7837 | 1     |     |
| Ca       | 0.3914 | 0.2349 | 0.4888 | 0.6617 | 1   |

At the same time, as shown in Table 1, since the development level of logistics in each region of China would be uneven with large variations, we used the system clustering method to classify the logistics in 30 regions of China, and the tree diagram of the classification results is shown in Figure 1.
In order to investigate the rationality of the variables, the one-way ANOVA was used. The results of the ANOVA are shown in Table 3. The five clustering variables (i.e., labor input, energy input, capital input, regional logistics added value, and CO2 emissions) were all significant at the 0.05 significance level, which confirmed that the five variables used for classification played a role in the classification [47].

Table 3. One-way ANOVA.

| Variables | Type       | Sum of Squares | df  | Mean Square | F     | Sig.   |
|-----------|------------|----------------|-----|-------------|-------|--------|
| L         | Between Groups | 2793.40        | 2   | 1396.70     | 16.94 | 0.000  |
|           | Within Groups   | 2225.83        | 27  | 82.44       |        |        |
|           | Total           | 5019.22        | 29  |             |       |        |
| E         | Between Groups  | 160,981.38     | 2   | 80,490.70   | 78.39 | 0.000  |
|           | Within Groups   | 27,722.90      | 27  | 1026.77     |        |        |
|           | Total           | 188,704.27     | 29  |             |       |        |
| C         | Between Groups  | 1,751,042.90   | 2   | 875,521.45  | 11.04 | 0.000  |
|           | Within Groups   | 2,141,385.05   | 27  | 79,310.56   |        |        |
|           | Total           | 3,892,427.95   | 29  |             |       |        |
| Ca        | Between Groups  | 361,367.24     | 2   | 180,683.62  | 6.06  | 0.007  |
|           | Within Groups   | 804,453.65     | 27  | 29,794.58   |        |        |
|           | Total           | 1,165,820.89   | 29  |             |       |        |
| G         | Between Groups  | 4,119,735.10   | 2   | 2,059,867.55| 17.50 | 0.000  |
|           | Within Groups   | 3,178,703.17   | 27  | 117,729.75  |        |        |
|           | Total           | 7,298,438.26   | 29  |             |       |        |

5. Efficiency Spatial Pattern and Analysis of China’s Logistics

5.1. Efficiency Spatial Pattern of China’s Logistics

The tree diagram of system clustering showed the classification of regional logistics efficiency in China. According to the results of system clustering, the logistics in 30 regions were divided into three categories: Category I included 13 regions, namely Hainan, Qinghai, Ningxia, Gansu, Xinjiang, Tianjin, Jiangxi, Guizhou, Anhui, Shaanxi, Guangxi, Chongqing,
and Yunnan; Category II included 4 regions, namely Jilin, Heilongjiang, Hubei, and Inner Mongolia; and Hebei and the other 13 areas belonged to Category III.

The statistical method of mean comparison was used to determine the classification characteristics. The specific values are shown in Table 4.

**Table 4. Comparison of mean values.**

| Groups | Mean L | Mean E | Mean C | Mean G | Mean Ca |
|--------|--------|--------|--------|--------|--------|
| 1      | 12.75  | 22.44  | 480.35 | 338.40 | 162.23 |
| N      | 13     | 13     | 13     | 13     | 13     |
| 2      | 23.23  | 241.82 | 708.19 | 599.22 | 317.14 |
| N      | 4      | 4      | 4      | 4      | 4      |
| 3      | 33.48  | 30.83  | 998.87 | 1128.5 | 396.39 |
| N      | 13     | 13     | 13     | 13     | 13     |
| Total  | 23.13  | 55.32  | 735.42 | 715.53 | 284.35 |
| N      | 30     | 30     | 30     | 30     | 30     |

The logistics in Category I were relatively low in terms of labor input, energy input, capital input, value-added output, and carbon dioxide emissions, which were far lower than the average. Most of the Category I regions are located inland, except Anhui, Jiangxi, Tianjin, and Hainan. The rest were underdeveloped areas in the West. The category II regions were close to the regional average in terms of labor input, capital input, industrial added value, and carbon dioxide emissions, but the energy input was far higher than the regional average. Except for Hebei, these areas are all distributed in the northeast. Their energy consumption was higher than the average level in China. For the Category III regions, except for the energy input, the other areas were higher than average. These areas are mainly distributed in the Yangtze River Delta and Pearl River Delta of China, and they are more economically developed.

5.2. Evaluation and Analysis on the Efficiency of China’s Regional Logistics Industry

To gain a deeper understanding of the logistics efficiency of each region, we used MAXDEA ultra 7.9 to measure the logistics efficiency of 30 regions in China from 2003 to 2016. After our calculations, we obtained the average value and ranking of the comprehensive efficiency and created a thermodynamic diagram. Figure 2 shows the distribution of the comprehensive efficiency and mean values in 30 regions. (Please refer to Table A1 in Appendix A for specific values.) Next, we conducted a multi-angle analysis of the comprehensive efficiency of the logistics in China.

5.2.1. Analysis on the Comprehensive Efficiency of China’s Regional Logistics

Firstly, the comprehensive efficiency of China’s logistics was not high, but it showed a slow upward trend. In general, considering the carbon constraints, the average efficiency of China’s logistics in 2003–2016 was 0.56. The highest results were in 2010 and 2015, where it was 0.62. More than one-half of the samples have never reached an industrial efficiency of 1, and among the regions that have, it had not been maintained over a long period. Concerning the national average, the logistics efficiency hovered around 0.5, which means that under this model, the actual output of the logistics in most regions of the sample did not reach 50% year-over-year. Other research during earlier periods under the same conditions did not reach 0.3, so, overall, it has improved, and the mean value of the research interval efficiency showed an upward trend, indicating that the efficiency was gradually increasing.
5.2.1. Analysis on the Comprehensive Efficiency of China’s Regional Logistics

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Secondly, the proportion of effective years of regional logistics efficiency was low, but the efficiency of regional logistics was quite different. Of the 420 technological efficiency samples, only 99 were effective (i.e., technological efficiency was greater or equal to 1, marked in red on the thermal diagram), shown in Figure 3. That is, the proportion of technological efficiency in 30 regions was only 23.57% in 2003–2016. There were four regions with average effective comprehensive efficiency in the study area, accounting for 13.33%, which were Guangdong, Fujian, Zhejiang, and Hebei. Only Fujian and Zhejiang achieved technological efficiency every year in 2003–2016. There were 8 regions that achieved or exceeded 50% technological efficiency, accounting for 26.67%; there were 14 regions that never achieved the technological efficiency, accounting for 46.67%; the remaining 8 regions only achieved the technological efficiency in 1–3 years, accounting for 26.67%. The proportion of units that had not achieved technological efficiency for more than half of the years from 2003 to 2016 reached 73.33%, which indicated that these areas continued to have significant issues in resource allocation capacity and resource utilization efficiency.

5.2.2. Analysis on the Spatial Pattern Evolution of Regional Logistics Efficiency

The top 10 efficiency rankings were two Category I regions, zero Category II regions, and eight Category III regions; in the 11–20 rankings, there were five Category I regions, one Category II region, and four Category III regions. In the last 10 rankings, there were six Category I regions, three Category II regions, and one Category III region. The overall level of logistics efficiency in Category III was relatively high. Half of Category I had a medium level of efficiency while the other half, similar to the Category II region, was low.
Based on the spatial distribution of regional logistics efficiency, among the 13 regions of Category III, 2 regions (Fujian and Zhejiang) achieved technological efficiency, 6 regions (Guangdong, Hebei, Beijing, Shanghai, Jiangsu, and Shandong) achieved technological efficiency more than half of the time, and the proportion of technological efficiency for more than one year was 61.54%; 3 regions (Henan, Hunan, and Liaoning) only achieved DEA effectiveness in 1–3 years, and the remaining 2 regions (Shanxi and Sichuan) never reached technology effectiveness. While four regions (Inner Mongolia, Hubei, Heilongjiang, and Jilin) in Category II never achieved technology effectiveness, the most effective years in Category I regions were few as well. Tianjin had the most, with an average annual value of 0.71, and for 5 out of 14 years, they achieved technology efficiency. The regions that achieved partial efficiency during the study period were: Guangxi, 4 years; Hainan and Guizhou, 2 years; and Hunan and Ningxia, 1 year. Regions such as Jiangxi, Anhui, Chongqing, Gansu, Shaanxi, Xinjiang, Yunnan, and Qinghai did not achieve this level in any year. Among the three types of regions, the effective proportion of logistics efficiency in the Category III region was the highest, which basically achieved half of the effective years. In the Category I region, only a few years were effective, while in the other half of the region, similar to the Category II region, the logistics efficiency had not reached technological efficiency. Therefore, there was a significant gap in the technological efficiency of logistics. During the statistical period, the technological efficiency in the Category III region was higher than both the average level of the Category II region and the Category I region taken together, and it was also higher than the national average.

5.2.3. Time Evolution Analysis on Comprehensive Efficiency of Regional Logistics

To clearly observe the time evolution of regional logistics efficiency, the efficiency trend charts during the research period are provided. The categories were grouped and sorted in descending order according to their logistics efficiency score based on the results from the system clustering analysis.

As shown in Figure 4, the areas with obvious upward trends of logistics efficiency included Beijing, Shanghai, Jiangsu, Liaoning, Guizhou, Anhui, and Beijing; Shanghai and Jiangsu had a more obvious upward trend of efficiency, among which Beijing maintained a stable upward direction since 2008. Whereas Shanghai had a relatively large upward trend in 2003–2006 and then a steady upward state, Jiangsu maintained an 8% efficiency increase rate prior to 2012. There were few regions showing a downward trend: Guangdong,
Shandong, and Henan. Guangdong and Shandong had an efficiency decline, but they began to stabilize and maintain an increasing trend after 2014. The logistics efficiency of the other regions showed a slight increase in fluctuations.

Generally speaking, the logistics efficiency in both the Category I and Category III high-efficiency areas were on the rise in the fluctuation. After 2010, it continued rising at different degrees. However, the lower efficiency areas of all the categories showed either a minor deterioration or remained at low levels without much change. Taking Beijing, Hubei, and Sichuan as examples, the GDP of these three provinces has exceeded CNY 800 billion, and the efficiency of logistics in Beijing was far higher than that in Hubei and Sichuan. This was due to the energy consumption and pollution emissions from logistics in Hubei and Sichuan being significantly higher than in Beijing: The average carbon emission of Beijing was 86.9 million tons while that of Hubei and Sichuan was 235.05 and 247.81 million tons, respectively. In addition, by building an “eco-city” in order to host the Olympic Games, Beijing made many improvements and innovations in carbon emissions. Resource input, a low utilization rate, and high emissions affect the growth of logistics efficiency, and technology and management levels also affect the change in industrial efficiency by varying degrees. To further study the variations in regional logistics efficiencies, we decomposed and analyzed the data.

6. Efficiency Decomposition and Analysis of Regional Logistics in China

The comprehensive technological efficiency (TE) of each region from 2003 to 2016 was decomposed into pure technological efficiency (PTE) and scale efficiency (SE). At the same time, to facilitate the analysis of the current efficiency changes and scale returns for each region, the efficiency of each region was separately decomposed, and the results are shown in Table 5. Technological efficiency was a comprehensive measure for the evaluation of resource allocation ability, resource utilization efficiency, and other capabilities of decision-making units. If an industry was at the forefront of production, the industry was technically efficient (technological efficiency was equal to 1). If the technological efficiency was less than 1, its influencing factors were various but could typically be categorized as either pure technological efficiency or scale efficiency. Next, the efficiency decomposition of regional logistics was analyzed.
Table 5. Regional logistics efficiency decomposition and evaluation.

| Regions   | 2003–2016 |       |       | Regions   | 2016 |       |       |
|-----------|-----------|-------|-------|-----------|------|-------|-------|
|           | TE        | PTE   | SE    |           | TE   | PTE   | SE    |
| Qinghai I | 0.15      | 1.19  | 0.12  | Yunnan I  | 0.11 | 0.27  | 0.42  |
| Yunnan I  | 0.16      | 0.28  | 0.26  | Qinghai I | 0.13 | 1.20  | 0.11  |
| Xinjiang I| 0.22      | 0.31  | 0.71  | Gansu I   | 0.15 | 0.33  | 0.46  |
| Shaanxi I | 0.25      | 0.31  | 0.80  | Shaanxi I | 0.24 | 0.32  | 0.74  |
| Gansu I   | 0.25      | 0.51  | 0.50  | Jilin II  | 0.24 | 0.35  | 0.68  |
| Jilin II  | 0.25      | 0.33  | 0.76  | Heilongjiang II | 0.26 | 0.32  | 0.80  |
| Heilongjiang II | 0.26 | 0.31  | 0.85  | Hainan I | 0.27 | 1.43  | 0.19  |
| Shanxi III| 0.31      | 0.36  | 0.88  | Xinjiang I| 0.29 | 0.40  | 0.72  |
| Hubei II  | 0.32      | 0.35  | 0.92  | Anhui I   | 0.30 | 0.40  | 0.74  |
| Chongqing I | 0.32  | 0.43  | 0.74  | Hubei II  | 0.34 | 0.36  | 0.93  |
| Inner mongol II | 0.35 | 0.38  | 0.92  | Inner mongol II | 0.34 | 0.38  | 0.89  |
| Sichuan III | 0.37  | 0.45  | 0.82  | Ningxia I | 0.37 | 1.45  | 0.25  |
| Ningxia I | 0.40      | 1.51  | 0.27  | Shanxi III| 0.37 | 0.45  | 0.83  |
| Anhui I   | 0.41      | 0.51  | 0.80  | Chongqing I| 0.38 | 0.51  | 0.75  |
| Guizhou I | 0.46      | 0.61  | 0.75  | Sichuan III| 0.41 | 0.44  | 0.95  |
| Hainan I  | 0.47      | 1.99  | 0.24  | Shandong III| 0.52 | 0.53  | 0.99  |
| Liaoning III | 0.47 | 0.50  | 0.95  | Hunan III | 0.52 | 0.55  | 0.96  |
| Hunan III | 0.54      | 0.60  | 0.90  | Henan III | 0.53 | 0.58  | 0.90  |
| Henan III | 0.55      | 0.59  | 0.93  | Jiangxi I | 0.55 | 0.92  | 0.60  |
| Jiangxi I | 0.56      | 1.10  | 0.51  | Tianjin I  | 0.66 | 1.11  | 0.59  |
| Guangxi I | 0.70      | 2.26  | 0.31  | Guangxi I | 0.77 | 2.97  | 0.26  |
| Tianjin I | 0.71      | 0.87  | 0.82  | Guizhou I | 1.01 | 1.03  | 0.97  |
| Shandong III | 0.86 | 0.99  | 0.87  | Guangdong III | 1.02 | 1.12  | 0.91  |
| Jiangsu III | 0.88   | 0.89  | 0.98  | Jiangsu I | 1.11 | 1.12  | 0.99  |
| Jiangsu III | 0.97   | 1.12  | 0.86  | Hebei III | 1.13 | 1.14  | 1.00  |
| Shanghai III | 0.99  | 1.07  | 0.93  | Shanghai III | 1.14 | 1.53  | 0.75  |
| Beijing III | 1.00   | 1.02  | 0.98  | Liaoning III | 1.18 | 1.20  | 0.98  |
| Hebei III | 1.00      | 1.17  | 0.95  | Fujian III | 1.20 | 1.23  | 0.98  |
| Zhejiang III | 1.11  | 1.17  | 0.98  | Fujian III | 1.22 | 1.35  | 0.90  |
| Fujian III | 1.15      | 1.17  | 0.98  | Fujian III | 1.22 | 1.33  | 0.92  |
| Guangdong III | 1.33  | 1.53  | 0.87  | Zhejiang III | 1.22 | 1.33  | 0.92  |
| Average   | 0.56      | 0.82  | 0.75  | Average   | 0.60 | 0.88  | 0.74  |

6.1. PTE Analysis of Regional Logistics

If the PTE of logistics in a region was $\geq 1$, it was considered to be pure scale effective; otherwise, it was invalid. The data in Table 5 show that during 2003–2016, the PTE value of 11 provinces in Guangdong, Fujian, Zhejiang, Hebei, Beijing, Shanghai, Guangxi, Jiangxi, Hainan, Ningxia, and Qinghai was greater than 1, and 36.67% of China’s regions realized PTE optimization, which indicated that the logistics input resources in these regions had been effectively utilized, along with the technological innovation, especially the innovation effect of logistics technology and emission reduction technology. In addition, the PTE value of 63.33% provinces was less than 1, indicating a regional imbalance. Yunnan, Heilongjiang, Shaanxi, Xinjiang, and Jilin ranked last in PTE values of 0.2844, 0.3068, 0.3072, 0.3076, and 0.334, respectively, indicating that these five regions lacked advanced logistics management technology and methods as well as the resources for allocation and integration. Therefore, more effort would need to be applied to improve the logistical efficiency in these regions.

6.2. Analysis on the Scale Efficiency of Regional Logistics

If the SE in a region was $\geq 1$, it was considered to be pure scale effective; otherwise, it was invalid. There were nine regions with an SE above 0.9, namely Jiangsu, Fujian, Hebei, Liaoning, Zhejiang, Beijing, Henan, Inner Mongolia, and Hebei. The development of logistics in these regions had made remarkable achievements in economic scale optimization. The industrial scale was relatively close to the most optimal production frontier scale, realizing more than 90% of the optimal efficiency that the region could achieve. The SE values of the other regions were low, especially in Qinghai, Hainan, Ningxia, Guangxi, and
Gansu. Their SE values were all below 0.5, indicating that the development scale of logistics in these regions needed to be optimized. In areas with a low SE, such as Qinghai, Ningxia, Hainan, and Guangxi, it indicated that while they had realized a reasonable allocation and utilization of the existing logistics resources, the scale of logistics was not large enough; therefore, their efficiency could be optimized by enlarging the scale of logistics.

6.3. Analysis on Scale Returns of Regional Logistics

Regarding scale efficiency, there were 378 samples with increasing returns to scale and 46 samples with decreasing returns to scale. Among them, the latter were distributed across 8 Category III regions, namely Shandong, Hebei, Guangdong, Zhejiang, Jiangsu, Liaoning, Shanghai, and Beijing, with 11, 8, 8, 7, 6, 3, 2, and 1 years, respectively, as shown in Table 6. It suggested that due to the further expansion of the scale of logistics in these areas, it had been difficult for all aspects of the industry to be effectively coordinated, and the management efficiency had been reduced, which had led to the diminishing state returns to scale. For example, the unreasonable division of labor among industries, the obstacles of logistics nodes and operation, and the asymmetry of all kinds of information needed in logistics decision-making and optimization contributed to poor decision-making, resulting in the decline of industrial operation efficiency and the rise of costs, etc. These regions should coordinate their industrial development, adjust their input factors, and avoid uncoordinated expansions.

Table 6. Regions and years of diminishing returns to scale.

| Regions     | Times | Years of Decreasing          |
|-------------|-------|------------------------------|
| Shandong III| 11    | 2005–2013                    |
| Hebei III   | 8     | 2004–2007, 2009, 2013–2015   |
| Guangdong III| 8   | 2008, 2010–2016              |
| Zhejiang III| 7     | 2003, 2011–2016              |
| Jiangsu III | 6     | 2005–2006, 2012–2014         |
| Liaoning III| 3     | 2004–2006                    |
| Shanghai III| 2     | 2007–2008                    |
| Beijing III | 1     | 2006                         |
| Total       | 46    | –                            |

However, in 2016, only Shandong and Zhejiang were in the area of diminishing returns to scale, indicating that although large-scale investment had been continuously applied, there was still a significant decline in returns to scale. It indicated that large-scale investment did not play a role. From the rankings of the added value of logistics, Guangdong, Jiangsu, Shandong, Hebei, Henan, and Zhejiang ranked in the top six in 2016. The other four regions with more output than Shandong and Zhejiang were still in the stage of increasing returns to scale, which reflected the overall management efficiency of logistics management and decision-making in these regions. In addition, the logistics in most areas of China were still in the stage of increasing returns to scale, which meant that under the existing industrial scale, the growth of factor input could result in a higher proportion of output level growth. However, Yunnan, Xinjiang, Shaanxi, Gansu, Jilin, Chongqing, Heilongjiang, Inner Mongolia, Anhui, Liaoning, and other regions were also in the stage of increasing returns to scale, but these regions had not yet reached the PTE optimum under the existing scale of logistics, which indicated that the integration and utilization of existing logistics resources were insufficient, and the focus should be on tapping the potential of existing logistics resources and improving logistics operation and management. We should consider expanding the scale of logistics after increasing the management and technology level.
6.4. Analysis on the Difference of TE in Regional Logistics

If the TE of logistics in a region was $\geq 1$, its comprehensive technology was considered to be effective, which indicated that the overall management and technological level of logistics were fully reflected; otherwise, it was invalid. As TE was divided into PTE and SE, the reasons for the differences in technological efficiency of the logistics among regions were examined according to these two aspects, as shown in Table 5.

First, there had to be effective PTE in the area where TE was effective (efficiency value was greater than or equal to 1). Whether it was the mean performance of the study interval or the data from the latest year, such as the mean performance of Guangdong, Fujian, and Zhejiang in 2003–2016, and the TE and PTE of Zhejiang, Beijing, Fujian, and Liaoning in 2016, they were both effective. However, for areas where PTE was effective, TE was not necessarily effective, such as Hebei, Beijing, Shanghai, Guangxi, Jiangxi, Hainan, Ningxia, and Qinghai in 2003–2016, and Guangxi, Tianjin, Ningxia, Hainan, and Qinghai in 2016. The reason was that the scale efficiency of these regions was not high, especially in Guangxi, Hainan, Ningxia, Qinghai, etc. The scale efficiency was below 0.4, which greatly reduced the effect of PTE, resulting in a comprehensive efficiency value under 1, and the efficiency optimization was not achieved. Therefore, the regional difference of PTE was determined to be the necessary condition for TE to be effective.

Second, a range of scale efficiency was required to ensure that the pure technological efficiency would play a role. From 2003 to 2016, there was good scale efficiency in the areas with TE efficiency. The lowest average was in Shanghai, but it also reached 0.8644. In 2016, except for Shanghai’s 0.7463, the scale efficiency of TE effective regions was above 0.9 while the pure technology efficiency was high, but the regions low in scale efficiency were also poor in performance. Therefore, a range of scale efficiency could ensure that PTE could play an effective role to improve production.

Third, PTE and SE had to reach a certain threshold simultaneously to achieve the technological effectiveness in production. Previously, we had found that, if the scale of PTE was not effective, the overall performance of TE was still invalid. Similarly, if the scale of logistics in a region was large enough but its PTE lagged behind, it could not employ the effectiveness of technology and realize output optimization. For example, from 2003 to 2016, the scale efficiency of the logistics in Henan, Liaoning, Inner Mongolia, and Hubei reached more than 90%. However, due to the lack of technology, its efficiency value hovered between 30% and 50%, resulting in a poor performance of overall efficiency.

In addition to the development of industrial scale and the promotion of scale efficiency, it would also be necessary to pay attention to the role of management and technology, make effective use of various inputs, ensure the coordination of production processes, and make scientific decisions regarding the optimal output. Therefore, further analysis regarding the rationality of factor input and output could provide additional insights for improvements to promote green efficiency and realize sustainable development in the logistics industry.

7. Slack Variable Analysis of Regional Logistics in Production Front

By projecting the production frontier of the logistics in each region, we could not only understand the use of its factor input, but we could also analyze the reasons for its ineffectiveness and determine the degree of its attribute value for improvement and the ideal value of input–output. According to the optimal input of each region obtained from the model results, the input redundancy rate was obtained by dividing the relaxation variables by the optimal inputs. If it was positive, it was input-redundant; if it was negative, it was an insufficient input. Similarly, the output redundancy rate was calculated. Table 7 shows the slack variable performance of logistics in 30 regions concerning input and output.
Table 7. Input and output optimization analysis of regional logistics.

| Regions      | L     | E   | C   | Ca  | G   | L   | E   | Ca  | G   |
|--------------|-------|-----|-----|-----|-----|-----|-----|-----|-----|
| Qinghai I    | −24.6 | 0.0 | −5.3 | −6.3 | 0.0 | −37.6 | 0.0 | 0.0 | 0.0 |
| Yunnan I     | 65.7  | 80.1 | 333.4 | 51.0 | 0.0 | 105.6 | 201.5 | 300.9 | 168.0 |
| Xinjiang I   | 150.2 | 392.5 | 88.9 | 257.7 | 0.0 | 108.5 | 521.8 | 89.2 | 78.3 |
| Shaanxi I    | 120.7 | 547.3 | 74.2 | 166.8 | 0.0 | 105.7 | 499.6 | 131.7 | 0.0 |
| Gansu I      | 35.0  | 232.9 | 23.3 | 15.2 | 0.0 | 44.2  | 3082.1 | 89.6 | 58.7 |
| Jilin II      | 53.4  | 2340.3 | 23.7 | 41.2 | 0.0 | 44.2  | 2335.6 | 48.9 | 151.1 |
| Heilongjiang II| 62.0 | 7749.5 | 16.2 | 34.8 | 0.0 | 80.9  | 2235.6 | 48.9 | 151.1 |
| Shanxi II    | 175.4 | 852.2 | 85.5 | 612.2 | 0.0 | 75.8  | 297.5 | 0.0 | 253.1 |
| Hubei II     | 84.6  | 2627.3 | 34.3 | 37.2 | 0.0 | 83.4  | 2137.2 | 43.9 | 59.0 |
| Chongqing I  | 27.9  | 51.4 | 19.6 | 4.4  | 0.0 | 87.5  | 283.7 | 20.4 | 14.7 |
| Inner mongol II| 12.1 | 756.6 | 23.7 | 41.2 | 0.0 | 44.2  | 3082.1 | 89.6 | 58.7 |
| Anhui I      | 13.0  | 89.7 | 32.9 | 105.7 | 0.0 | 91.7  | 449.4 | 29.0 | 83.4 |
| Guizhou I    | 13.9  | 119.6 | 45.2 | 30.8 | 0.0 | 89.0  | 526.6 | 0.0 | 67.0 |
| Jilin II      | 17.5  | 852.2 | 85.5 | 612.2 | 0.0 | 75.8  | 297.5 | 0.0 | 253.1 |
| Hubei II     | 84.6  | 2627.3 | 34.3 | 37.2 | 0.0 | 83.4  | 2137.2 | 43.9 | 59.0 |
| Chongqing I  | 27.9  | 51.4 | 19.6 | 4.4  | 0.0 | 87.5  | 283.7 | 20.4 | 14.7 |
| Inner mongol II| 12.1 | 756.6 | 23.7 | 41.2 | 0.0 | 44.2  | 3082.1 | 89.6 | 58.7 |
| Anhui I      | 13.0  | 89.7 | 32.9 | 105.7 | 0.0 | 91.7  | 449.4 | 29.0 | 83.4 |
| Guizhou I    | 13.9  | 119.6 | 45.2 | 30.8 | 0.0 | 89.0  | 526.6 | 0.0 | 67.0 |
| Jilin II      | 17.5  | 852.2 | 85.5 | 612.2 | 0.0 | 75.8  | 297.5 | 0.0 | 253.1 |
| Hubei II     | 84.6  | 2627.3 | 34.3 | 37.2 | 0.0 | 83.4  | 2137.2 | 43.9 | 59.0 |
| Chongqing I  | 27.9  | 51.4 | 19.6 | 4.4  | 0.0 | 87.5  | 283.7 | 20.4 | 14.7 |
| Inner mongol II| 12.1 | 756.6 | 23.7 | 41.2 | 0.0 | 44.2  | 3082.1 | 89.6 | 58.7 |
| Anhui I      | 13.0  | 89.7 | 32.9 | 105.7 | 0.0 | 91.7  | 449.4 | 29.0 | 83.4 |
| Guizhou I    | 13.9  | 119.6 | 45.2 | 30.8 | 0.0 | 89.0  | 526.6 | 0.0 | 67.0 |
| Jilin II      | 17.5  | 852.2 | 85.5 | 612.2 | 0.0 | 75.8  | 297.5 | 0.0 | 253.1 |
| Hubei II     | 84.6  | 2627.3 | 34.3 | 37.2 | 0.0 | 83.4  | 2137.2 | 43.9 | 59.0 |
| Chongqing I  | 27.9  | 51.4 | 19.6 | 4.4  | 0.0 | 87.5  | 283.7 | 20.4 | 14.7 |

7.1. From the Perspective of Investment

7.1.1. First, There Has Been Insufficient Labor Input in Areas Where PTE Was Effective, and SE Was Low

In 2003–2016, Qinghai, Ningxia, Hainan, Guangxi, Hebei, and Zhejiang had different degrees of insufficient labor input (the input redundancy rate was negative). These were divided into two groups, the first of which included Qinghai, Ningxia, Hainan, and Guangxi. On one hand, in the process of economic development, the labor force in these areas constantly moved outward, which led to a shortage in the labor force for local logistics and affected the expansion of industrial scale. Table 5 shows that the SE values of these regions were very low. On the other hand, it verified the impact of insufficient labor input on their scale expansion, resulting in poor TE performance even though these regions had good PTE. The second group was Hebei and Zhejiang, which were located in an area with labor influx. Theoretically, the population from other provinces had provided abundant labor resources for the development of logistics. However, as the scale of logistics in these two areas had reached super efficiency, both PTE and SE were close to or at the production frontier; therefore, they needed additional labor support to match their growth. However, Zhejiang’s insufficient labor was further improved in 2016, so the technological efficiency increased to 1.2, as compared to the average value of 1.1 in 2003–2016, which realized the operation of super efficiency industries and super efficiency output. In 2016, the added value beyond the frontier was CNY 9.75 billion, which was CNY 7.201 billion more than CNY 2.549 billion in 2003–2016, reflecting that Zhejiang Province had effectively allocated logistics input and output in 2016 and optimized their overall efficiency.
7.1.2. Second, in the Areas Where PTE Was Effective and TE and SE Were Both Low, There Had Been Insufficient Energy and Capital Investment Problems

In Table 5, the areas with insufficient energy and capital investment were Ningxia, Hainan, Jiangxi, Guizhou, Guangxi, etc. These areas had low overall efficiency and did have the advancements or innovations that could be found in other, better performing regions. We attributed this to the slow economic development and the lack of cohesion in these areas to attract talents, capital, and energy; the insufficient input of factors impacted their industrial scale expansion and further inhibited industrial technology and efficiency improvements. The low efficiency weakened the attraction of logistics and lessened their appeal for new talent and energy investment and therefore formed a vicious circle.

7.1.3. Thirdly, There Were Different Degrees of Redundancy in Labor, Energy, and Capital Investment in Areas Where PTE Was Ineffective

By comparing Tables 5 and 7, we found that the mean values of 2003–2016 or the annual values of 2016 had little impact, with the exception of Qinghai, Ningxia, Hainan, Jiangxi, Guangxi, Shanghai, Hebei, Zhejiang, Fujian, and Guangdong, in which they had the effective PTE mean value. Other regions outside Qinghai, Ningxia, Hainan, Tianjin, Guangxi, Guizhou, Guangdong, Jiangsu, Hebei, Shanghai, Beijing, Zhejiang, and Guangdong had similar redundancy rates in Table 7, there was little difference in the redundancy rates of the labor force in various regions. The areas with high redundancy rates were the areas with underdeveloped economies in Category I. Due to the lack of industrial development speed, and efficiency, they were unable to utilize the labor force input for the existing scale, such as Xinjiang, Shanxi, Shaanxi, etc., which were unable to realize the reasonable allocation of logistics personnel input. The energy input redundancy rate was the highest among all input factors. These regions basically had more than 50% of the energy input redundancy rate, especially in Xinjiang, Shaanxi, and Inner Mongolia, other regions. The energy redundancy rate was more than 100%, which indicated that reducing energy input and optimizing the energy consumption structure were the typical challenges in the development of low-carbon logistics economy in these regions. In terms of capital redundancy, Yunnan, Sichuan, and Gansu had higher investment redundancy. Reviewing the efficiency performance of these three regions, we found that both SE and PTE in Yunnan and Gansu were at a very low level, while SE in Sichuan had reached more than 0.8, but their PTE lagged behind. Yunnan and Gansu were unable to allocate a large amount of capital investment due to their lack of technology and management resources, and their scale was not large enough. Although the logistics in Sichuan are on a large scale, the technological and management improvements have not been adequately improved and have therefore affected the industrial capital investment.

7.2. From the Perspective of Output
7.2.1. First, There Were Undesirable Output Redundancies in the Areas That Had Not Realized Effective TE, Especially in the Areas with Low PTE

From Table 7, in 2003–2016, there were excessive emissions in most regions to varying degrees, with the exception of Qinghai, Hainan, and Guangxi. According to the 2016 carbon emission data, only Hainan and Guangxi’s low-carbon logistics industries achieved frontier efficiency. In addition, the areas with low PTE, such as Shanxi, Shaanxi, and Heilongjiang, reached over 100% in their carbon emission redundancy rate. The high emission redundancy rate indicated that the lack of investment in low-carbon technology research and development and the inefficient industrial structure were the main factors of the poor ecological performance in these areas. To achieve rapid and effective development in a low-carbon economy, research and development in low-carbon technology is crucial. As compared to the average data in 2003–2016 and the annual data in 2016, the overall carbon emission in 2016 was much lower than the average data from 2003–2016, which indicated that China had improved their low-carbon logistics. Optimizing the industrial layout,
adjusting the industrial structure, and reasonably controlling high industrial emissions were effective methods for reaching China’s low-carbon logistics target.

7.2.2. Second, TE Effective Areas Have Achieved Super Efficiency Output

Table 7 shows that the areas with a TE higher than, or close to, 1 have different degrees of super-efficiency output, such as Tianjin, Shandong, Jiangsu, Shanghai, Beijing, Zhejiang, Fujian, and Guangdong, in 2003–2016. Other provinces, except for Shandong, also maintained their super-efficiency output in 2016. According to Table 5, the TE in Shandong was around 0.5262 in 2016, so it did not fully optimize the output of factor input. Considering these areas with super-efficiency output, all of them belonged to the Category III economically developed areas or to coastal areas, with the exception of Tianjin, and they were at the national level of advanced logistics technology, human resource management, and production management. To achieve frontier efficiency in the industry, it would be necessary to effectively integrate talents, technology, and management to achieve super efficiency output.

Overall, the comprehensive efficiency of China’s logistics varied significantly from region to region: the input–output combinations of the Category III regions were relatively good, the input–output combinations of the Category I and II regions were poor, and approximately 50% of the region had a large degree of resource redundancy. The government should consider adjusting the structural state of input elements according to the scale of the local industry and management levels and implement a reasonable development plan to achieve green and sustainable logistics.

8. Efficiency Type Analysis of Logistics Based on Low-Carbon Economy

After analyzing the efficiency and frontier of each region, we used the data of technological efficiency and carbon dioxide emissions to analyze the quadrant chart of 30 regions in 2003–2016 and classified the efficiency of the logistics. The results are shown in Figure 5.

High-efficiency areas: This included the fourth quadrant of high-efficiency, low-emission areas and the first quadrant of high-efficiency, high-emission areas. The former included Fujian, Shanghai, Beijing, Guangdong, Zhejiang, and Tianjin, while the latter included Shandong and Hubei. The high-efficiency areas included economically developed areas in China such as those near the Yangtze River Delta and the Pearl River Delta. These areas had better transportation infrastructures, abundant logistics resources, and advanced industrial technologies, so the logistics industry had developed rapidly. This indicated that regional logistics efficiency was significantly positively correlated with regional economic development. The stronger the comprehensive strength of the regional economy was, the greater the space for logistics development and the higher the logistics efficiency would be, and vice versa. Therefore, by relying on strong economic and technological advantages, these provinces should be committed to the research, development, innovation, and application of low-energy technologies to further promote and lead the promotion of low-energy technologies in national logistics as well as to reduce the carbon emissions of the whole industry. For high-emission areas, such as Shanxi, Inner Mongolia, Shandong, and so on, the high consumption of logistics produced high carbon emissions, but the input–output values were relatively reasonable, thus achieving high logistics efficiency.
After analyzing the efficiency and frontier of each region, we used the data of technological efficiency and carbon dioxide emissions to analyze the quadrant chart of 30 regions in China from 2003 to 2016 and classified the efficiency of the logistics. The results are shown in Figure 5.

![Quadrant of low carbon efficiency of regional logistics](image)

**Figure 5.** Quadrant of low carbon efficiency of regional logistics. The circle drawn with the first and third quartiles of the horizontal and vertical axes are mainly to make it easier to identify areas close to the quadrant transition boundaries.

Low-efficiency areas: This included the low-efficiency and low-emission areas in the third quadrant and the low-efficiency and high-emission areas in the second quadrant. The former included Shaanxi, Anhui, Heilongjiang, Xinjiang, Hubei, Sichuan, Jilin, Hunan, Guizhou, Yunnan, Gansu, Ningxia, Jiangxi, Guangxi, Qinghai, Chongqing, and Hainan, while the latter included Shanxi, Inner Mongolia, Liaoning, and Henan. For low-efficiency and low-emission areas, their weak economic foundations and slow development of logistics resulted in low resource utilization. Although the low-carbon emissions of logistics had been realized, the logistics output was insufficient. Therefore, the overall efficiency was not high. These areas should focus on the establishment of coordinated development in logistics and actively strive for financial and technological support from central and local logistics. In the low-efficiency and high-emission areas, the lack of economic development, logistics resource endowment, and logistics talents meant that they were unable to reach the production frontier. Without advanced low-carbon technology, there were serious carbon emission issues that led to low industrial efficiency. Liaoning, Henan, Hebei, and Jiangsu all maintained the middle level between efficiency and emissions. The logistics industry in these areas was developing rapidly, and there was a lot of investment in logistics resources. However, in the process of logistics development, low-carbon operation had not yet been achieved. The sustainable development of the logistics industry had been hindered, and the input–output factor should be further improved.

The efficiency and efficiency zones of logistics under carbon constraints were concentrated in the Category III region, namely the fourth quadrant, which was the benchmark for the other regions. The first and second quadrants were the focus to improve the efficiency of China’s logistics, particularly in emission reduction. The third quadrant had high values, and the logistics efficiency under carbon constraints was relatively low, which was the key issue for improvement. Only by implementing policies according to regional needs and challenges can we promote the sustainable development of China’s logistics industry.
9. Conclusions and Policy Implications

This study examined the efficiency of China’s regional logistics under carbon constraints by using the super-SBM model and analyzing the changes in logistics efficiency across time and location.

This study first examined the reasons for the regional differences in efficiency using decomposition and calculation. After further investigating the slack variables in the production frontier of each region, we classified and analyzed the factors involved in a low-carbon economy. This study used 420 sample data from 2003 to 2016, and the contribution of this study includes the following:

Since joining the WTO (World Trade Organization), the comprehensive efficiency of China’s logistics has not been high. The proportion of effective years of regional logistics in comprehensive efficiency was low, and there were obvious deficiencies between regions due to the low level of PTE and low SE in most areas. During the studied time period, the efficiency of logistics in most regions showed an upward trend. In a few areas, there was a slight deterioration in efficiency or little change whatsoever. However, the comprehensive efficiency of logistics has gradually been improving. According to the technological efficiency decomposition, approximately one-third of China’s logistics achieved PTE optimization, and two-thirds of China’s logistics was lagging behind in terms of logistics management techniques and methods. This has led to wasted logistics resources and inefficient logistics output, with varying degrees of redundancy in labor, capital, and energy inputs. In two-thirds of the regions, the SE value was low, approximately 0.5 or less, and the scale of logistics needed to be optimized. Approximately 90% of the region’s logistics efficiency was in the stage of increasing returns to scale. The other 10% of the regions were in the stage of diminishing returns to scale, but they had achieved super-efficient output. At the same time, we found that in the process of logistics development, low-carbon operation had not been realized. High efficiency, low efficiency, and high emissions existed simultaneously, and the input–output factors need to be balanced.

Therefore, China’s logistics should further encourage the coordinated development of inter-regional logistics. The government should consider the factors involved in high-efficiency and low-emission areas, provide national and regional logistics nodes for the surrounding areas, and promote the interconnection of logistics infrastructure and information-resource sharing. The local government should provide corresponding industrial support policies to improve the developmental environment of logistics, further encourage industrial technology innovation, and accelerate the progress of cutting-edge technology. However, under carbon constraints, the efficiency of the Category III regional logistics was generally high while other regions were relatively low. The difference in technological efficiency between regions continues to deteriorate. It indicates that there are strong mobile barriers between China’s logistics regions. Only a few economically developed regions have benefited from technological progress and efficiency improvements. The transition process has had a stronger divergent trend than the technological progress. If the region cannot break through development barriers such as ineffective government policies, technological efficiency will continue to decline. Therefore, we should encourage innovation while promoting inter-regional industrial technology education and knowledge sharing, which would not only improve the productivity level of logistics in other regions but also increase the return of innovation and generate stronger innovation incentives. By improving the developmental ability of regional logistics, the regional economy will inevitably be improved with complementary advantages and mutual benefits. Therefore, for the areas that have not optimized their technological efficiency and have insufficiently integrated their resource utilization, they should consider the potential existing logistics resources, improve the level of logistics operation, and raise their management level. After the management and technological level have been addressed, the scale of logistics can be expanded. For areas with low scale efficiency, it may be possible to increase capital and energy input, to expand the industrial scale and achieve scale efficiency, and to pay attention to the role of management and technology in scale operation, according to the needs.
of regional development. At the same time, they should focus on the role of management and technology in scale operations. Therefore, the rational use of various elements, the coordination of capital and technology, the reduction in investment redundancy, and the acceleration of the application and development of energy-saving and emission-reduction technologies should be the key turning points for the change from extensive to intensive.

This study employed the super SBM method to decompose the efficiency data from a temporospatial perspective. It also contributed a multi-perspective analysis and the decomposition of the influencing factors of regional differences in logistics efficiency, and analyzed the redundancy of various factor inputs.

As with any study, this one had some limitations that could be addressed and improved upon in future research. First, the sample interval was from 2003 to 2016, so the more recent developments and changes in China’s regional logistics efficiency could not be considered, which limited our analysis. Second, the analysis was based on the time-series mean of the regional logistics industry, and only longitudinal research was performed without a horizontal analysis. The influence of other factors such as institutions and urban–rural differences was not considered, so the impact of various factors on industrial efficiency may be inaccurate. Since regional and institutional differences exist in the efficiency of low-carbon logistics, further research should be conducted concerning the impact of carbon emissions on logistics efficiency under urban versus rural logistics, as well as the impact of carbon emissions on logistics efficiency under different systems.

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Appendix A

Table A1. Efficiency value and ranking of logistics considering undesirable output.

| Regions     | 2003  | 2004  | 2005  | 2006  | 2007  | 2008  | 2009  | 2010  |
|-------------|-------|-------|-------|-------|-------|-------|-------|-------|
| Guangdong III | 1.85  | 1.80  | 1.72  | 1.66  | 1.60  | 1.30  | 1.48  | 1.18  |
| Fujian III   | 1.15  | 1.14  | 1.17  | 1.17  | 1.20  | 1.20  | 1.14  | 1.13  |
| Zhejiang III | 1.00  | 1.12  | 1.01  | 1.07  | 1.03  | 1.08  | 1.05  | 1.07  |
| Hebei III    | 1.07  | 0.54  | 0.56  | 1.05  | 1.01  | 0.80  | 1.07  | 1.08  |
| Beijing III  | 0.25  | 0.34  | 0.54  | 1.07  | 1.07  | 1.01  | 1.05  | 1.17  |
| Shanghai III | 0.35  | 0.35  | 0.72  | 1.09  | 1.04  | 1.01  | 1.01  | 1.07  |
| Jiangsu III  | 0.37  | 0.47  | 0.46  | 0.63  | 0.73  | 0.62  | 1.03  | 1.10  |
| Shandong III | 0.72  | 0.64  | 1.17  | 1.12  | 1.17  | 1.18  | 1.15  | 1.04  |
| Tianjin I    | 0.32  | 1.04  | 0.45  | 0.52  | 0.41  | 0.42  | 0.65  | 1.03  |
| Guangxi I    | 0.37  | 0.40  | 0.39  | 0.44  | 0.40  | 0.36  | 0.42  | 1.56  |
| Jiangxi I    | 0.34  | 0.34  | 0.58  | 0.55  | 0.55  | 0.55  | 0.75  | 0.69  |
| Henan III    | 0.33  | 0.38  | 0.48  | 0.54  | 1.01  | 1.08  | 0.66  | 0.52  |
| Hunan III    | 0.29  | 0.48  | 0.51  | 1.02  | 0.64  | 0.39  | 0.55  | 0.51  |
| Liaoning III | 0.53  | 0.40  | 0.38  | 0.32  | 0.34  | 0.23  | 0.36  | 0.36  |
### Table A1. Cont.

| Regions             | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 |
|---------------------|------|------|------|------|------|------|------|------|
| Hainan I            | 0.33 | 1.25 | 1.27 | 0.65 | 0.36 | 0.32 | 0.32 | 0.33 |
| Guizhou I           | 0.15 | 0.17 | 0.28 | 0.30 | 0.31 | 0.23 | 0.58 | 0.57 |
| Anhui I             | 0.28 | 0.33 | 0.57 | 0.61 | 0.65 | 0.49 | 0.43 | 0.44 |
| Ningxia I           | 0.14 | 0.15 | 0.27 | 0.30 | 0.29 | 0.24 | 0.49 | 0.56 |
| Sichuan III         | 0.33 | 0.42 | 0.56 | 0.55 | 0.50 | 0.41 | 0.32 | 0.32 |
| Inner mongolia II   | 0.16 | 0.18 | 0.32 | 0.39 | 0.38 | 0.34 | 0.42 | 0.40 |
| Chongqing I         | 0.18 | 0.20 | 0.36 | 0.42 | 0.33 | 0.29 | 0.37 | 0.35 |
| Shanxi III          | 0.18 | 0.19 | 0.39 | 0.46 | 0.49 | 0.26 | 0.26 | 0.30 |
| Hubei II            | 0.19 | 0.00 | 0.30 | 0.31 | 0.30 | 0.30 | 0.35 | 0.32 |
| Heilongjiang II     | 0.25 | 0.27 | 0.33 | 0.29 | 0.28 | 0.18 | 0.21 | 0.21 |
| Jilin II            | 0.19 | 0.18 | 0.27 | 0.31 | 0.32 | 0.23 | 0.28 | 0.24 |
| Gansu I             | 0.09 | 0.12 | 0.25 | 0.33 | 0.40 | 0.31 | 0.36 | 0.30 |
| Shaanxi I           | 0.19 | 0.27 | 0.29 | 0.27 | 0.27 | 0.17 | 0.29 | 0.26 |
| Xinjiang I          | 0.15 | 0.19 | 0.21 | 0.27 | 0.27 | 0.17 | 0.20 | 0.19 |
| Yunnan I            | 0.17 | 0.28 | 0.19 | 0.20 | 0.20 | 0.18 | 0.15 | 0.14 |
| Qinghai I           | 0.13 | 0.16 | 0.16 | 0.17 | 0.18 | 0.11 | 0.17 | 0.19 |
| Mean                | 0.40 | 0.46 | 0.54 | 0.60 | 0.59 | 0.52 | 0.58 | 0.62 |

| Regions            | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | Mean | Rank |
|---------------------|------|------|------|------|------|------|------|------|
| Guangdong III       | 1.07 | 1.09 | 1.10 | 0.83 | 0.86 | 1.02 | 1.33 | 1    |
| Fujian III          | 1.09 | 1.09 | 1.11 | 1.13 | 1.16 | 1.20 | 1.15 | 2    |
| Zhejiang III        | 1.08 | 1.14 | 1.16 | 1.26 | 1.23 | 1.22 | 1.11 | 3    |
| Hebei III           | 1.08 | 1.06 | 1.20 | 1.18 | 1.14 | 1.13 | 1.00 | 4    |
| Beijing III         | 1.25 | 1.23 | 1.28 | 1.23 | 1.20 | 1.22 | 0.99 | 5    |
| Shanghai III        | 1.09 | 1.11 | 1.11 | 1.31 | 1.19 | 1.14 | 0.97 | 6    |
| Jiangsu III         | 1.11 | 1.24 | 1.17 | 1.10 | 1.14 | 1.11 | 0.88 | 7    |
| Shandong III        | 1.13 | 0.54 | 0.65 | 0.51 | 0.50 | 0.52 | 0.86 | 8    |
| Tianjin I           | 1.03 | 0.63 | 1.03 | 0.68 | 1.10 | 0.66 | 0.71 | 9    |
| Guangxi I           | 1.07 | 0.80 | 1.07 | 0.66 | 1.01 | 0.77 | 0.70 | 10   |
| Jiangxi I           | 0.49 | 0.71 | 0.66 | 0.55 | 0.53 | 0.55 | 0.56 | 11   |
| Henan III           | 0.31 | 0.35 | 0.42 | 0.38 | 0.52 | 0.53 | 0.55 | 12   |
| Hunan III           | 0.38 | 0.43 | 0.59 | 0.63 | 0.58 | 0.52 | 0.54 | 13   |
| Liaoning III        | 0.36 | 0.35 | 0.37 | 0.42 | 1.04 | 1.18 | 0.47 | 14   |
| Hainan I            | 0.31 | 0.27 | 0.25 | 0.27 | 0.27 | 0.27 | 0.47 | 15   |
| Guizhou I           | 0.43 | 0.43 | 0.46 | 0.46 | 1.02 | 1.01 | 0.46 | 16   |
| Anhui I             | 0.34 | 0.33 | 0.33 | 0.35 | 0.32 | 0.30 | 0.41 | 17   |
| Ningxia I           | 0.44 | 1.04 | 0.46 | 0.44 | 0.41 | 0.37 | 0.40 | 18   |
| Sichuan III         | 0.23 | 0.22 | 0.24 | 0.29 | 0.37 | 0.41 | 0.37 | 19   |
| Inner mongolia II   | 0.40 | 0.39 | 0.43 | 0.41 | 0.36 | 0.34 | 0.35 | 20   |
| Chongqing I         | 0.26 | 0.25 | 0.32 | 0.40 | 0.38 | 0.38 | 0.38 | 21   |
| Shanxi III          | 0.24 | 0.25 | 0.32 | 0.32 | 0.35 | 0.37 | 0.31 | 22   |
| Hubei II            | 0.30 | 0.28 | 0.39 | 0.45 | 0.41 | 0.34 | 0.30 | 23   |
| Heilongjiang II     | 0.22 | 0.26 | 0.30 | 0.30 | 0.26 | 0.26 | 0.26 | 24   |
| Jilin II            | 0.24 | 0.23 | 0.29 | 0.26 | 0.25 | 0.24 | 0.25 | 25   |
| Gansu I             | 0.28 | 0.27 | 0.28 | 0.18 | 0.18 | 0.15 | 0.25 | 26   |
| Shaanxi I           | 0.22 | 0.23 | 0.26 | 0.26 | 0.23 | 0.24 | 0.25 | 27   |
| Xinjiang I          | 0.17 | 0.22 | 0.24 | 0.24 | 0.24 | 0.29 | 0.22 | 28   |
| Yunnan I            | 0.10 | 0.11 | 0.13 | 0.13 | 0.13 | 0.11 | 0.16 | 29   |
| Qinghai I           | 0.15 | 0.12 | 0.12 | 0.13 | 0.15 | 0.13 | 0.15 | 30   |
| Mean                | 0.56 | 0.56 | 0.59 | 0.57 | 0.62 | 0.60 | 0.56 | -    |

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