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Measurement on the Efficiency of Regional Logistics Industry under the Constraint of Low Carbon

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Abstract: *The traditional efficiency measurement of the logistics industry does not consider the problem of dioxide emissions. This paper proposes the total factor productivity (CLP) of the logistics industry under the constraint of carbon intensity. Based on the construction of the panel data of the logistics industry in 30 provinces and regions in China from 2005 to 2012, the environmental DEA technology and the directional distance function method are applied to conduct an empirical analysis of the growth sources and regional differences of the total factor productivity of China's logistics industry under the constraints of carbon intensity. . The results show that the logistics industry's total factor productivity under the carbon intensity constraint has an average annual growth rate of 1.9%, which is higher than that without considering the carbon constraint; the logistics industry productivity index under the carbon intensity constraint is consistent with the carbon intensity target, and the logistics industry's total factor productivity has improved , The carbon intensity decreases; the improvement of logistics productivity mainly depends on the progress and innovation of logistics technology; under the constraint of carbon intensity, there is convergence in the logistics productivity of the eastern region, the difference in the central region is expanding, and the western region is shrinking.*

Keywords: *Transportation economy; total factor productivity of logistics industry; low carbon; environmental DEA technology; technological progress*

1. Introduction

The logistics industry is an important service industry for the development of the national economy, and its level of development has become one of the important indicators for measuring the comprehensive strength of a country or region. At the same time, the logistics industry is also the main industry in China's energy consumption and occupies a special position in the low-carbon economy. In recent years, the logistics industry's dependence on energy such as gasoline, kerosene and diesel has increased year by year. How to reduce carbon emissions in the logistics field is an inevitable requirement for promoting the economic development of low-carbon logistics. The early literature research on the efficiency of the logistics industry focused on the analysis of the efficiency of the transportation industry. Oum et al. (1992) [1] proposed the concept of transportation productivity and proposed measurement methods, and the domestic scholar Yu Siqin et al. (2004) [2] calculated various transportation departments in China. Productivity from 1990 to 2000. Liu Yuhai et al. (2008)[3] analyzed the productivity of China's road transportation industry from 2000 to 2004. With the rapid development of the logistics industry, research on the efficiency of the logistics industry has gradually increased in recent years. Tian Gang et al. (2009)[4] and Wang Weiguo et al. (2012)[5] constructed panel data on the logistics industry in China's provincial regions, and analyzed the total factor productivity of the logistics industry in each region and the source of its growth momentum. Tang Jianrong et al. (2013) [6] used the undesired output of carbon dioxide emissions as an input variable for the first time to measure the pure technical efficiency, scale efficiency and overall efficiency of the logistics industry. Han Biao (2017) first studied the relationship between the factor substitution elasticity of the logistics industry and industrial growth. However, none of the output of current research models incorporates undesired factors such as environmental pollution into the measurement. Therefore, this paper studies carbon emissions as an undesired output into the model measurement, using the direction distance function and environmental DEA technology to measure the total factor productivity of the logistics industry.

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2. Methods and models

2.1 Manquist-Rohenberg Productivity Index Model

Chung et al. (1997) proposed the Manquist-Röhnberg productivity index based on the environmental DEA technology and the direction distance function, which is called LP for short.The problem of measuring total factor productivity under the condition of reducing undesired output is solved.

Consider the production function $F(X)$ of the gross value of a regional logistics industry. Where X represents the factor input and $X=(K,L,E)\in R_N^+$, K represents capital input, L represents labor input, E represents energy input. Y and C are obtained through production. Among them, Y is beneficial to the growth and development of the logistics industry. It is an expected output, and the larger it is expected, the better; and C is an undesired output accompanying the production process of Y, and it is expected that the smaller the better. The set of all possible outputs including expected output and undesired output is called the production feasible set, denoted as P, based on the non-parametric analysis framework of environmental DEA technology, assuming that there are a total of $i=1,\cdots I$ regions as decision-making units, the $i=1,\cdots I$ of input and output value of each region is (K_i,L_i,E_i,Y_i,C_i), and the intensity variable ϖ_i is the weight assigned to each decision-making unit when constructing the production frontier, which can be expressed by the following linear programming.

$$P=\left\{(K,L,E,Y,C):\sum_{i=1}^{M}\varpi_i K_i\le K\right.$$

$$\sum_{i=1}^{M}\varpi_i L_i\le L$$

$$\sum_{i=1}^{M}\varpi_i E_i\le E$$

$$\sum_{i=1}^{M}\varpi_i Y_i\ge Y$$

$$\left.\sum_{i=1}^{M}\varpi_i C_i=C;\varpi_i\ge 0,i=1,\cdots I\right\}\quad(1)$$

The directional distance function refers to a representative function that describes the optimal proportion of output index variables (or input index variables) based on a fixed input (or output) under a certain level of production technology, which can be expressed by the following formula :

$$\overrightarrow{D_o}(K,L,E,Y,C;d_Y,-d_C)=\sup\{\lambda:(Y+\lambda d_Y,C-\lambda d_C)\in P(K,L,E,Y,C)\}\quad(2)$$

In formula (2), the distance function value λ represents the distance between the observation value (Y,C) of the decision-making unit and its projection $(Y+\lambda d_Y,C-\lambda d_C)$ on the production frontier. The direction vector $d=(d_Y,-d_C)$ determines the direction of the efficiency measurement, that is, the direction of output expansion or decrease. The direction in which the expected output (Y) expands is d_Y, and the direction vector (C) is not the direction in which the expected output $-d_C$ decreases. The direction distance function is realized in the undesired output. The maximum expansion of expected output under the constraints. According to the different values of the direction vector $d=(d_Y,-d_C)$, this paper sets two directional distance function situations.

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Case 1: Assumption $d=(Y,0)$, without considering the impact of undesired output (C), can be expressed by the following mathematical programming formula:

$$\overrightarrow{D}_o^t\left(K_i^t, L_i^t, E_i^t, 0; Y_i^t, 0\right)=Max\lambda$$

$$s.t. \quad \sum_{i=1}^{M}\varpi_i^t K_i^t \le K_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t L_i^t \le L_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t E_i^t \le E_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t Y_i^t \ge (1+\lambda) Y_i^t$$

$$\varpi_i \ge 0, i=1,\cdots M \quad (3)$$

Scenario 2: Assuming $d=(Y,-C)$, and undesired output (C) has weak disposal, the direction vector $d=(Y,-C)$ requires the same proportion to increase the value-added of the logistics industry and reduce carbon dioxide emissions, which can be expressed by the following mathematical programming formula:

$$\overrightarrow{D}_o^t\left(K_i^t, L_i^t, E_i^t, 0; Y_i^t, -C_i^t\right)=Max\lambda$$

$$s.t. \quad \sum_{i=1}^{M}\varpi_i^t K_i^t \le K_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t L_i^t \le L_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t E_i^t \le E_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t Y_i^t \ge (1+\lambda) Y_i^t$$

$$\sum_{i=1}^{M}\varpi_i^t C_i^t = (1-\lambda) C_i^t$$

$$\varpi_i \ge 0, i=1,\cdots M \quad (4)$$

The inequalities about factor input (K,L,E) and expected output (Y) indicate that they are freely disposable. The equation for the undesired output (C) shows that the undesired output (C) is weakly disposed. The function value $\lambda=0$ means that the decision-making unit is at the forefront of production, and its production is efficient. The larger the function value λ, the farther the decision-making unit is from the production frontier, the lower the efficiency.In the case of low-carbon constraints, the Manquist-Röhnberg productivity index LP of the i decision variable can be expressed as:

$$LP_{i,t}^{t+1}=\left\{\frac{\left[1+\vec{D}_o^{t}\left(K_i^t,L_i^t,E_i^t,Y_i^t,C_i^t;Y_i^t,-C_i^t\right)\right]}{\left[1+\vec{D}_o^{t}\left(K_i^{t+1},L_i^{t+1},E_i^{t+1},Y_i^{t+1},C_i^{t+1};Y_i^{t+1},-C_i^{t+1}\right)\right]}\times\frac{\left[1+\vec{D}_o^{t+1}\left(K_i^t,L_i^t,E_i^t,Y_i^t,C_i^t;Y_i^t,-C_i^t\right)\right]}{\left[1+\vec{D}_o^{t+1}\left(K_i^{t+1},L_i^{t+1},E_i^{t+1},Y_i^{t+1},C_i^{t+1};Y_i^{t+1},-C_i^{t+1}\right)\right]}\right\}^{\frac{1}{2}}$$

The total factor productivity index LP can be decomposed into the continuous product of the change in efficiency (EF) and the change in technological progress (TE):

$$LP = EF \times TE \quad (6)$$

$$EF_{i,t}^{t+1}=\frac{1+\vec{D}_o^{t}\left(K_i^t,L_i^t,E_i^t,Y_i^t,C_i^t;Y_i^t,-C_i^t\right)}{1+\vec{D}_o^{t+1}\left(K_i^{t+1},L_i^{t+1},E_i^{t+1},Y_i^{t+1},C_i^{t+1};Y_i^{t+1},-C_i^{t+1}\right)} \quad (7)$$

$$TE_{i,t}^{t+1}=\left\{\frac{\left[1+\vec{D}_o^{t+1}\left(K_i^t,L_i^t,E_i^t,Y_i^t,C_i^t;Y_i^t,-C_i^t\right)\right]}{\left[1+\vec{D}_o^{t}\left(K_i^t,L_i^t,E_i^t,Y_i^t,C_i^t;Y_i^t,-C_i^t\right)\right]}\right. \quad (8)$$

$$\left.\times\frac{\left[1+\vec{D}_o^{t+1}\left(K_i^{t+1},L_i^{t+1},E_i^{t+1},Y_i^{t+1},C_i^{t+1};Y_i^{t+1},-C_i^{t+1}\right)\right]}{\left[1+\vec{D}_o^{t}\left(K_i^{t+1},L_i^{t+1},E_i^{t+1},Y_i^{t+1},C_i^{t+1};Y_i^{t+1},-C_i^{t+1}\right)\right]}\right\}^{\frac{1}{2}} \quad (9)$$

2.2 Convergence analysis

σ convergence analysis is to study the variation of the dispersion of total factor productivity LP of the logistics industry between different regions over time. If the dispersion gradually becomes smaller, it means that the dispersion of productivity is shrinking and tends to converge. If the dispersion becomes larger, it means that the dispersion of productivity is expanding and tends to diverge. The convergence analysis of total factor productivity σ under the constraint of carbon intensity studied in this paper can be expressed as follows:

$$\sigma_t=\sqrt{\frac{1}{M-1}\sum_{i=1}^{M}\left(LP_{i,t}-\overline{LP_t}\right)^2} \quad (10)$$

Among them, $LP_{i,t}$ represents the total factor productivity of the logistics industry in the i region in the t period, and $\overline{LP_t}$ is the average value of the total factor productivity of the logistics industry in all M regions in the t period. When $\sigma_{t+1}<\sigma_t$, it means that the dispersion of total factor productivity of China's logistics industry is shrinking under the constraint of carbon intensity, and there is σ convergence.

3. Model indicators and data

This article collects the logistic factor input (the capital investment in the logistics industry, the number of employees in the logistics industry, and the logistics energy consumption), expected output (the added value of the logistics industry) and undesired output (carbon dioxide emissions) of the logistics industry in 30 provinces and regions in China from 2011 to 2018. the amount).

The capital investment in the logistics industry is calculated according to the total investment in the transportation, storage and postal industries in the fixed asset investment of the whole society by major industries. Liu Binglian (2009) adopts the method of using fixed asset investment as a substitute for capital stock and adopts 2011 The fixed asset investment price index with the year as the base period

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(2011=100) is converted to a constant price. The number of employees in the logistics industry is calculated by selecting the China Statistical Yearbook (2012-2019) to divide the data, dividing the railway transportation industry, road transportation industry, urban public transportation industry, air transportation industry, pipeline transportation industry, loading, unloading and handling, other transportation services, and postal services. Karma is accumulated and added. Regarding the energy consumption indicators of the logistics industry, this article selects the seven energy sources that consume the largest proportions in the transportation, storage and postal industries, including coal, gasoline, kerosene, diesel, fuel oil, liquefied petroleum gas, and natural gas. (2012-2019) The statistics of primary energy consumption in various regions are used as energy input, and different types of energy consumption are unified and converted into standard coal.

Regarding output indicators, the logistics industry's added value (logistics industry GDP) calculated in this paper is selected from the China Statistical Yearbook (2012-2019) by the transportation, storage and postal industry based on the GDP of the three industries and regions, and based on 2010 The annual constant price is converted into the output value of the logistics industry in each year and each region. Carbon dioxide emissions are calculated based on the energy consumption of various regions in the China Energy Statistical Yearbook (2012-2019) and the various energy emission coefficients on the Carbon Dioxide Information Analysis Center. The statistical summary of the sample data is shown in Table 1.

Table 1 Sample description

	index	Number of samples	average value	Standard deviation	Max	Minimum
K	Capital investment in logistics industry (100 million yuan)	240	507	364	1743	35
L	Number of employees in the logistics industry at the end of the year (10,000 people)	240	23	13	72	4
E	Energy consumption of logistics industry (10,000 tons of standard coal)	240	752	552	2609	40
Y	Added value of logistics industry (100 million yuan)	240	554	438	2328	30
C	Carbon dioxide emissions (ten thousand tons)	240	404	305	1505	15

According to the classification standard of the National Bureau of Statistics of China, the 30 provinces excluding Tibet are divided into three major regions. The eastern region includes 11 provinces including Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong, and Hainan. The central region includes 8 provinces including Shanxi, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan. The western region includes 11 provinces or autonomous regions in Inner Mongolia, Guangxi, Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang.

4. Total factor productivity measurement of the logistics industry

4.1 Comparison of production factors of logistics industry in different situations

Calculate the logistics industry productivity in the two scenarios (2011-2018), expressed by LP and CLP respectively, and the results are shown in Table 2. It can be seen that, regardless of the logistics carbon intensity constraint, the average annual growth rate of logistics industry productivity in China's 30 provinces and autonomous regions during 2011-2018 was 0.8%. With the addition of carbon dioxide emission constraints, the average annual growth rate of logistics industry productivity during 2011-2018 was 2 %, higher than the case where the carbon strength constraint is not considered. This shows that the productivity of the logistics industry under carbon intensity constraints is higher than that without carbon constraints. Because the former considers the contribution of the production process to environmental improvement as the supply and demand for productivity, while the latter ignores environmental goals in the productivity evaluation.

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Table 2 Comparison of logistics productivity

situation	index	2012	2013	2014	2015	2016	2017	2018	average value
situation1	LP	0.934	0.998	1.036	0.996	1.018	1.025	1.047	1.008
situation2	CLP	0.962	1.014	1.032	1.005	1.022	1.029	1.073	1.019

Figure 1 shows the change trend between carbon intensity and accumulated logistics industry productivity from 2011 to 2018. The accumulated CLP can intuitively reflect whether the productivity of phase $t+1$ has increased or regressed. If the accumulated CLP of phase $t+1$ is larger than that of phase t, it indicates that the logistics industry productivity of phase $t+1$ has increased compared with the previous period. From 2012 to 2014, the carbon intensity of unit logistics GDP decreased from 0.867 tons/10,000 yuan to 0.755 tons/10,000 yuan, and there was a temporary increase in 2014-2016, increasing to 0.836 tons/10,000 yuan, and it showed a downward trend in 2016-2018. In 2012, it was reduced to 0.724 tons/10,000 yuan. From the overall trend, the carbon emissions per unit of logistics GDP has shown a downward trend in recent years. By comparing the carbon intensity and accumulated logistics industry productivity from 2011 to 2018, it can be found that the accumulated CLP can better explain the changes in carbon intensity. When CLP is improved, the carbon intensity decreases, and vice versa.

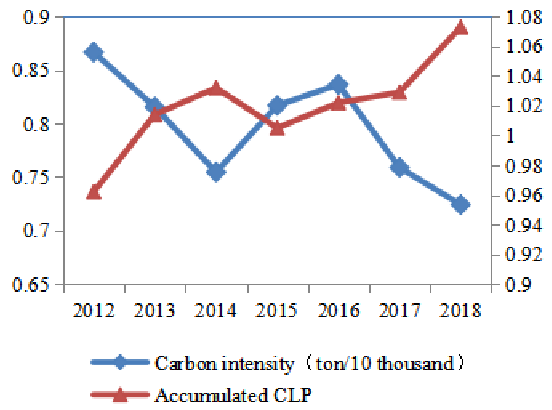

Fig.1 Change of carbon intensity and cumulative CLP (2012-2018)

4.2 Decomposition of logistics industry productivity under carbon intensity constraints

The productivity of the logistics industry under the constraint of carbon intensity is decomposed into an efficiency change index (EF) and a technological progress index (TE). From Table 2 and Table 3, it can be found that the average annual growth rate of logistics industry productivity from 2011 to 2018 is 1.9%, which is mainly due to the technological progress of the logistics industry. Among them, the average annual growth rate of technological progress is 1.5%, and the improvement of logistics efficiency affects the impact of carbon constraints. The logistics industry's productivity growth has not contributed much, with an average annual growth rate of about 0.4%. The main reason is that since 2000, the rapid development of industrialization and urbanization in China and the continuous upgrading of industrial structure have stimulated the strong growth of logistics demand. In addition, governments at all levels have invested a large amount of funds and manpower in the logistics industry, and the introduction of logistics-related policies. The effect of technological innovation is obvious. In 2005, China proposed a low-carbon economic transformation strategy, focusing on energy conservation, and logistics as one of the main energy consumption industries. In addition to the output value of the logistics industry, each region focuses on energy conservation and low-carbon technology, reducing carbon dioxide emissions, and innovation in information technology. Effectively promote the progress of total factor productivity in the logistics industry.

Table 3 Efficiency change index and technological advancement index

	2011	2012	2013	2014	2015	2016	2017	average
EF	0.974	1.008	1.012	0.996	1.007	1.008	1.025	1.004
TE	0.988	1.006	1.02	1.009	1.015	1.021	1.047	1.015

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4.3 Comparison of regional logistics industry productivity under carbon intensity constraints

Regardless of low-carbon constraints and low-carbon constraints, the productivity of the logistics industry in each region is greater than 1, which shows that in recent years, as the logistics industry has been vigorously developed in various regions, the production efficiency of the logistics industry has increased. Comparing the logistics productivity of the three major regions (Table 4), it is found that the eastern region is the highest, and the western region is slightly higher than the central region. This also shows that the western development strategy is proposed. The economic development of the western region stimulates the logistics demand in the western region. The investment in logistics infrastructure in the western region has effectively promoted the efficiency of the logistics industry in the western region. Comparing the efficiency change indexes of the three major regions, it is found that the eastern region is the highest, the western region is in the middle, and the central region is the lowest; the technical progress index of each region is compared, and the eastern region is the highest, the central region is in the middle, and the western region is the lowest. This also shows that the western region is lagging behind in logistics technology innovation. In the eastern and western regions. In addition, the technical progress index of each region under the low-carbon constraint has been significantly improved compared with that without considering the low-carbon constraint. This also proves that the increase in the productivity of the logistics industry in recent years mainly depends on the progress and innovation of logistics technology, and the development of low-carbon logistics economy. Supported by the innovation of low-carbon technology and logistics technology.

Table 4 Total productivity of regional logistics (2005-2012)

	situation1			Situation2		
	EF	TE	LP	EF	TE	CLP
All	1.002	1.006	1.008	1.004	1.015	1.019
east	1.005	1.012	1.017	1.007	1.023	1.030
Central	0.995	1.007	1.002	0.997	1.015	1.012
west	1.004	0.999	1.003	1.006	1.007	1.013

4.4 Convergence analysis

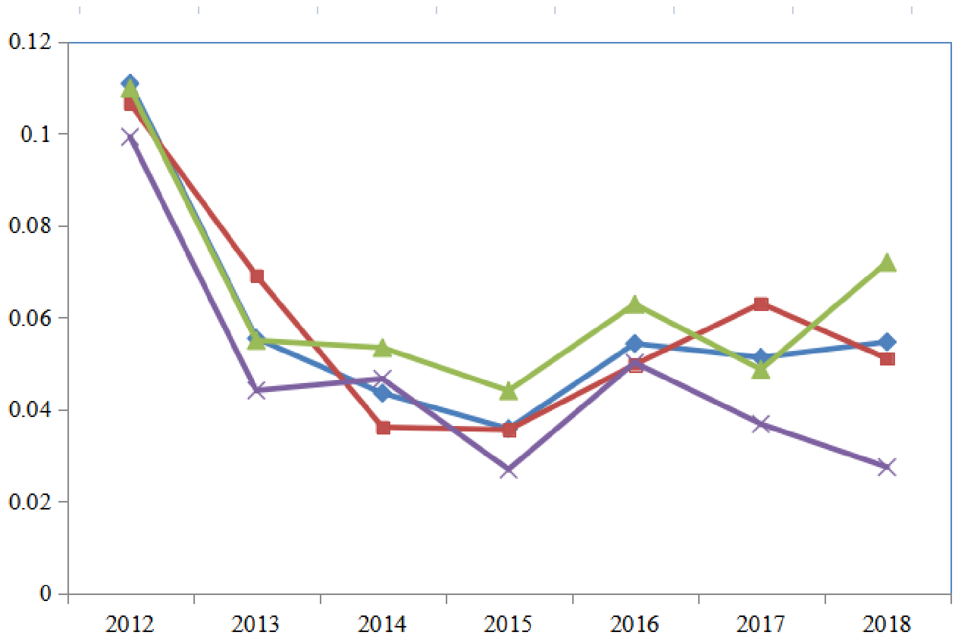

Fig.2 σ convergence results

Figure 2 shows the change of the standard deviation of logistics industry productivity in my country as a whole and in the three major regions of eastern, central and western China over time. From a national perspective, 2011-2018 showed a first decline, then a slight increase, and stabilized. The logistics productivity standard deviation of the eastern and central regions under the low-carbon constraint is significantly higher than that in the western region, which indicates that the logistics productivity differences of the provinces under the low-carbon constraint in the eastern and central regions are larger than those in the western region. In terms of sub-regions, the three major regions have a sharp decline during the period from 2011 to 2015. After a slight rebound in 2015, the central region has shown a clear divergence trend after 2015. Low-carbon inter-regional constraints on logistics productivity The degree of disparity is widening, while the logistics productivity under the carbon intensity constraint in the eastern region is convergent, and the logistics productivity under the carbon intensity constraint in the western region is convergent, indicating that the direct logistics productivity gap between provinces in the western region is gradually decreasing.

5. Conclusion

This paper uses the directional distance function and environmental DEA technology to construct the productivity of China's logistics industry under carbon intensity constraints, and corrects the distortion caused by ignoring carbon emissions in the traditional model. This paper finds that the productivity of the logistics industry that emphasizes environmental regulation is higher than that that does not consider the environment. The situation of regulation; the logistics industry productivity measurement is in line with the carbon intensity target. The cumulative logistics industry productivity can better explain the changes in carbon intensity. The logistics industry's productivity has improved, and the carbon intensity has decreased; the logistics industry's productivity increased by 1.9 per year from 2011 to 2018. %, of which logistics technology progress has an average annual growth rate of 1.5%, and the improvement of logistics efficiency has an average annual growth rate of about 0.4%. The improvement of logistics industry productivity mainly depends on logistics technology progress and innovation; the logistics industry productivity and logistics technology progress index in the eastern region are both the highest, while the logistics industry productivity in the western region is in the middle, and the logistics technology progress index is the lowest, indicating that the western region is in logistics technology innovation On the one hand, it lags behind the eastern and western regions; under the constraint of carbon intensity, the logistics industry in the eastern region has a convergence of productivity, the difference in the central region is widening, and the western region is shrinking.

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