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Analysis of the Operational Efficiency Measurement of Domestic Logistics Enterprises Against the Background of a Low-Carbon Economy

-- Based on Three-stage Data Envelopment Analysis Model

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Abstract. As an indispensable link between low-carbon economic activities, the green development of logistics enterprises determines their market competitiveness and industry development ability. In this paper, 80 domestic logistics enterprises identified in 2022 are selected as objects, and the three-stage data envelope analysis (DEA) method is used to construct the enterprise operation efficiency evaluation index system with the input-output data of 2017–2021. The results show that the overall operating efficiency of domestic logistics enterprises is not high. In 2017, the comprehensive technical efficiency and pure technical efficiency of effective companies reached their peaks, accounting for 22.5% and 35%, respectively. The scale efficiency of effective companies only accounted for 35%. The company's technology and management caliber are negatively impacted by external environmental conditions. There are redundancies in operating input and unreasonable allocations of operating resources. According to the analysis results, this paper puts forward some improvement suggestions for the sustainable development of domestic logistics enterprises from both the government and enterprises.

Keywords: Low-Carbon Economy; Operational Efficiency Measurement; Domestic Logistics Enterprises Against; Three-stage Data Envelopment Analysis Model; Sustainable Development; Green Development.

1. Introduction

A low-carbon economy is one that attains sustainable economic growth through cutting back on fossil fuel consumption and carbon emissions. In this context, logistics enterprises, as an indispensable part of economic activities, play an important role in achieving the goal of a low-carbon economy. China has implemented several pertinent rules and regulations to enhance and expedite the growth of the logistics sector since the "13th Five-Year Plan" era. The Opinions on Promoting High-Quality Development of Logistics to Promote the Formation of a Strong Domestic Market were released in 2019 by the National Development and Reform Commission. Clearly put forward in the future for a long period of time to "promote the high-quality development of the logistics industry" as an important goal to foster the modernization of logistics infrastructure and enhance the climate for investments in logistics. In recent years, with the support of national policies, a large number of domestic logistics enterprises have emerged and thrived. However, compared with developed countries, the development quality of China's logistics enterprises is not high enough; some enterprises have a lack of professional logistics talents, serious waste of resources, and other problems[1]. Operation efficiency is an important standard to measure the health of enterprise development, which is of great significance to improving the overall development level of China's logistics industry. As a result, this study establishes the three-stage data envelopment analysis (DEA) model, ascertains the input, output, and environmental variables, evaluates and contrasts the management effectiveness of our nation's logistics companies against the backdrop of a low-carbon economy, and, on the basis of this, offers pertinent recommendations to encourage our nation's logistics companies to enhance their quality and efficiency.

2. Literature Review

In the context of transitioning to a low-carbon economy, the operational efficiency of logistics companies is crucial for fostering environmentally friendly and sustainable economic growth at a national level. The current research emphasis is on employing scientific methodologies to assess enterprise efficiency and produce unbiased evaluation outcomes. Key areas of study in this field include developing evaluation criteria and techniques for measuring the efficiency of logistics companies.

2.1. Management Efficiency Evaluation Methods of Logistics Enterprises

Various domestic methodologies are available for assessing the operational efficiency of logistics enterprises, including one-stage DEA, three-stage DEA, and the Malmquist index method, among others. For instance, Cao Bingru et al.[2] discovered a positive spatial correlation in logistics efficiency among provinces and cities within the Yangtze River Economic Belt through the use of the DEA model, ArcGIS, and spatial autocorrelation analysis. Similarly, Li Jia[3] examined the operational efficiency of 38 listed logistics companies in China, employing DEA, cross-efficiency, and the Malmquist method, which revealed fluctuations in the management and operational capabilities of logistics enterprises in the country. In another study, Huang Ningning[4] utilized a DEA model to analyze the overall operational efficiency of listed logistics enterprises in the Shenzhen-Shanghai region, uncovering issues such as underutilization of resources and excessive input. Mo Xiumei[5] analyzed the operating efficiency of China's listed circulation enterprises with the help of three-stage DEA model and found that the operating efficiency of China's other circulation enterprises except the logistics industry has not improved significantly in the past ten years. Li Na et al.[6] combined the BCC model with the Malmquist index model to evaluate the efficiency of the logistics industry in 18 provinces along the "Belt and Road," highlighting a decline in total factor productivity within the sector. Lastly, Wu Zongze et al.[7], through the DEA-BCC and Malmquist index models, identified scale efficiency as a primary factor limiting operational efficiency, both statically and dynamically.

While the three-stage DEA method may yield efficiency values with significant errors and limitations, the first-stage DEA method may overlook the influence of random factors and environmental variables. When compared to alternative evaluation methods, the three-stage DEA method is better suited to providing a more precise assessment of the internal management practices of the evaluation subject. Consequently, this study opts to utilize the three-stage DEA method for evaluating the operational efficiency of logistics enterprises in Ningbo City.

2.2. Construction of Operation Evaluation Index System

Currently, the operational efficiency evaluation index system for enterprises primarily consists of two key components: factor input and performance output. In terms of input, factors such as labor and capital are emphasized, while output focuses on profitability and operational capacity. For instance, Chen Ting[8] analyzed the operational efficiency of listed logistics companies in China by utilizing indicators like main business costs, net fixed assets, management expenses, total employee salaries as input factors, and main business income, net profit as output factors. As low-carbon economies gain importance, energy consumption factors have now become essential input indicators. Dong Feng et al.[9] incorporated indicators such as carbon dioxide emissions from the logistics industry, fixed asset input in logistics, and total wages of logistics industry workers to evaluate the efficiency of China's inter-provincial logistics sector. Similarly, Sun Yu[10] selected carbon dioxide emissions, total turnover, and value added by the logistics sector as output indicators, and energy consumption, fixed asset investment, and the number of logistics personnel as input indicators.

3. Research Methods

Data Envelopment Analysis (DEA) is a method used to evaluate the relative efficiency of decision-making units (DMUs) that have multiple inputs and outputs. The traditional DEA model does not account for the influence of environmental variables and random interferences on the efficiency results of each DMU. To address this issue, the three-stage DEA model eliminates interference factors during the second stage by refining the SFA regression analysis. Subsequently, during the third stage of the DEA model, the adjusted indicators are reintroduced for a comparative analysis, aiming to enhance the accuracy in determining the true efficiency levels of each DMU.

In the initial stage, the BCC model with variable returns to scale is chosen, and DEAP2.1 software is employed to input the original data for each DMU into the traditional DEA model. This process is utilized to calculate the initial comprehensive efficiency, pure technical efficiency, scale efficiency, and derive the input relaxation variables for each DMU. The formula is as follows:I'm sorry for the abrupt ending earlier. Here is the revised continuation of the paragraph:

$$min\, \theta - \varepsilon(\hat{e}^T S^- + \hat{e}^T S^+)$$

$$s.t. \begin{cases} \sum_{j=1}^{n} X_j \lambda_j + S^- = \theta X_0 \\ \sum_{j=1}^{n} Y_j \lambda_j - S^+ = Y_0 \\ \lambda_j \geq 0, S^-, S^+ \geq 0 \end{cases}$$

Where, the decision unit is represented by $j = 1,2,\cdots,n$ X, and the input and output vectors are represented by X and Y. If $\theta = 1$, $S^- = S^+ = 0$, then the DMU is DEA valid. If $\theta = 1$, $S^- \neq 0$ or $S^+ \neq 0$, then the DMU is weak DEA effective. If $\theta < 1$, then the DMU is non-DEA efficient. The efficiency value calculated by BCC model is comprehensive technical efficiency (TE), which can be further decomposed into pure technical efficiency (PTE) and scale efficiency (SE), that is $\mathrm{TE} = \mathrm{SE} * \mathrm{PTE}$.

In the subsequent stage, the innovation input from the initial phase is adjusted according to the regression outcomes of the Stochastic Frontier Analysis (SFA) model, ensuring that all subjects under study are standardized within the same operating environment for efficiency computation. The calculation formula is detailed as follows:My apologies for the abrupt ending. Here is the continuation of the revised paragraph:

$$x_{ij}^A = x_{ij} + \left[max_j\{z_j, \hat{\beta}^l\} - z_j\hat{\beta}^l\}\right] + \left[max_j\{\hat{V}_{jk}\} - \hat{V}_{jk}\right]$$

In the above formula: x_{ij}^A is the adjusted input; $x_{ij}$is the input before adjustment; $\left[max_j\{z_j, \hat{\beta}^l\} - z_j\hat{\beta}^l\}\right]$ adjusts the standard external environmental factors for all decision units; $\left[max_j\{\hat{V}_{jk}\} - \hat{V}_{jk}\right]$ is placing all study subjects at the same level of random luck.

The input variables and environment variables determined in the initial phase were designated as explanatory and explanatory factors, respectively. By utilizing Frontier4.1 software, the input variables were refined to exclude environmental variables and random factors.

During the third stage, the input value that has been adjusted in the preceding phase supplants the initial input value. This adjusted input value, in combination with the original output value, is once again integrated into the traditional DEA model. Utilizing DEAP2.1 software, the efficiency is recalculated, consequently deriving the efficiency outcomes for each DMU while accounting for the influence of random errors and environmental factors.

4. Data Source and Index Selection

4.1. Data Sources

The research focuses on a sample of 80 domestic logistics enterprises distinguished in 2022, termed as the "sample enterprises." Cross-sectional data from 2017 to 2021 encompassing key metrics such as main business income, net profit, total carbon emissions of listed companies (in tons), total employee compensation, net fixed assets, main business costs, and the years of establishment for each enterprise have been selected as the primary research dataset. The primary data sources utilized include the China Logistics Yearbook, the China Statistical Yearbook, and similar credible sources.

Table 1. Listed domestic logistics companies and their subdivisions

Railway transportation industry G53	000557 Western Chuangchuang Railway, 601006 Daqin Railway, 600125 Tielong Logistics, 601333 Guangzhou-Shenzhen Railway
Road Transport Industry G54	000088 Yantian Port, 600368 Wuzhou Transportation, 000429 Guangdong Expressway A, 600377 Ninghu Expressway, 000548 Hunan Investment, 600548 Shenzhen Expressway, 000755 Shanxi Road Bridge, 600561 Jiangxi Changyun, 000828 Dongguan Holdings, 600611 Mass Transportation, 000885 Chengfa Environment, 6 00650 Jinjiang Online, 000900 Modern Investment, 600676 Traffic Shares, 002357 Fulin Transport Industry, 600834 Shentong Metro, 002627 Three Gorges Tourism, 601107 Sichuan Chengyu, 002682 Longzhou Shares, 601188 Longjiang Transportation, 200429 Guangdong Expressway B, 601518 Jilin Expressway, 600012 Wantong Expressway, 603069 Haiqi Group, 600020 Zhongyuan Expressway, 603223 Hengtong Shares, 600035 Chutian Expressway, 603813 Yuanshang Shares, 600106 Chongqing Road and Bridge, 900914 JinOnline B, 600269 Ganyue Expressway
Water transport industry G55	000520 Changhang Phoenix, 600575 Huaihe Energy Source, 000582 Beibu Gulf Port, 600717 Tianjin Port, 000905 Xiamen Port, 601000 Tangshan Port, 001872 China Merchants Port, 601008 Lianyungang, 002040 Nanjing Port, 601018 Ningbo Port, 002320 Haixia Stock, 6012 28 Guangzhou Port, 201872 Zhaobang B, 601326 Qinport Shares, 600017 Rizhao Port, 601872 Zhaobang Ships, 600018 Shanghai Port Group, 601880 Liao Port shares, 600026 Zhongyuan Sea Energy, 603167 Bohai Ferry, 600190 Jinzhou Port, 900952 Jingang B Shares, 600279 Heavy Qinggang Port
Air Transport G56	000089 Shenzhen Airport, 600897 Xiamen Airport, 000099 CITIC Haizhi, 601021 Spring Airlines, 600009 Shanghai Airport, 601111 Air China, 600029 Southern Airlines, 603885 Juneyao Airlines, 600115 China Eastern Airlines
Stevedoring and transportation agency G58	603128 China Trade Logistics, 603871 Jiayou International
Warehousing G59	002492 Hengji Daxin, 600794 Bonded Technology, 300013 Xinning Logistics, 603066 Yinfei Storage, 300240 Feilida, 603535 Jiacheng International, 600787 China Reserve Shares
Postal industry G60	002120 Yunda Shares, 600233 YTO Express, 002352 SF Holdings, 603056 Deppon Shares

4.2. Index Selection

4.2.1. Selection of Input/Output Variables

The choice of indicators plays a pivotal role in determining the ultimate assessment outcomes for evaluating the operational efficiency of logistics enterprises. This study utilizes main business revenue and net profit as output parameters. Additionally, main business costs and net fixed assets are designated as capital input indicators, while total employee salaries are identified as labor input indicators. Furthermore, the total carbon emissions (in tons) of listed companies are included as energy consumption factors (refer to Table 2).

Table 2. Explanatory quantity of input-output index for operational efficiency evaluation of logistics enterprises

Categories	Dimensions	Specific indicators	Number
Operating input	Capital input	Main business costs	X_1
		Net fixed assets	X_2
	Labor input	Total employee salaries	Y_1
	Factors of energy consumption	Total carbon emissions of listed companies (metric tons)	Y_2
Operating output	Operational capacity	Income from main business	Y_3
	Profitability	Net profit	Y_4

4.2.2. Environment Variable Selection

Environmental variables are external factors that have the potential to impact operational efficiency, yet are beyond the control of the decision-making unit. As such, their influence on operational efficiency assessments should be omitted during the calculation process. By drawing insights from studies on operational efficiency across various industries and fields, and taking into account the unique attributes of domestic logistics enterprises, six environmental variables have been identified. These variables are detailed in Table 2.

Table 3. Selection of environmental variables of innovation efficiency of technology enterprises in universities and colleges

Types of variables	Indicators	Specific variables	ID
Environment variables	Business life	The number of years the business has been established	Z_1
	Total Assets	Total business assets	Z_2
	Regional scientific and technological development level	R&D expenditure	Z_3
	Level of regional economic development	Per capita GDP of the region where the enterprise is located	Z_4
	Policy support	The proportion of transportation expenditure in the provincial region where the enterprise is located in the total local fiscal expenditure	Z_5
	Fixed assets of logistics industry	Total route Length	Z_6

5. Analysis of Empirical Results

5.1. The First Stage: Analysis of Traditional DEA Model Results

This study employs the BCC model in DEAP2.1 software to assess the operational efficiency of 80 sample companies spanning from 2017 to 2021. The indicator data are processed and utilized to determine the values of comprehensive technical efficiency, pure technical efficiency, and scale efficiency. Comprehensive technical efficiency serves as a gauge of the sample companies' capacity to optimize resource allocation, while pure technical efficiency primarily reflects the current management practices and technological proficiency within the sample company. Scale efficiency, on the other hand, highlights the variance between the actual scale and the optimal scale under identical competitive circumstances.

Table 4. Efficiency measurement results of sample enterprises in the first stage

		Comprehensive technical efficiency		Pure technical efficiency		Scale efficiency	
		Quantity	Percentage	Amount	Percentage	Amount	Percentage
2017	Valid	18	22.50%	28	35.00%	18	22.50%
	Ineffective	62	77.50%	52	65.00%	62	77.50%
2018	Valid	15	18.75%	25	31.25%	16	20.00%
	Ineffective	65	81.25%	55	68.75%	64	80.00%
2019	Valid	12	15.00%	24	30.00%	14	17.50%
	Ineffective	68	85.00%	56	70.00%	66	82.50%
2020	Valid	14	17.50%	26	32.50%	28	35.00%
	In vain	66	82.50%	54	67.50%	52	65.00%
2021	Valid	14	17.50%	24	30.00%	21	26.25%
	Ineffective	66	82.50%	56	70.00%	59	73.75%

Table 4 illustrates the overall operational efficiency distribution for the sample companies from 2017 to 2021. In the initial stage, excluding environmental considerations, the collective operational efficiency of the selected sample firms appears to be subpar. Notably, there were 18 companies out of 80 achieving comprehensive technical efficiency values of 1 in 2017, representing 22.50% of the total. However, this figure gradually decreased to 15% in 2019 before dipping slightly to 14% in 2020 and remaining unchanged in 2021. This indicates that only a limited number of enterprises within the sample have attained a high level of management proficiency. For pure technical efficiency, 28 companies reached their peak performance in 2017, accounting for 35% of the sample. Subsequently, between 2018 and 2021, there was a varying trend with levels stabilizing around 25%. This trend suggests that many enterprises are facing deficiencies in internal operations and management, leading to challenges in maximizing output from input utilization. Moreover, the proportion of companies demonstrating scale efficiency and effectiveness remained low, peaking at 35.00%. This indicates that the overall production scale efficiency among the sample companies is modest, with many facing issues related to scale inefficiency or underutilization.

5.2. The Second Stage: Analysis of SFA Regression Results

During this phase, the focus shifts to evaluating the influence of external environmental factors on the sample companies. Frontier4.1 software is utilized to conduct Stochastic Frontier Analysis (SFA) regression analysis, with the input index relaxation variable obtained in 2021 from the initial stage serving as the explained variable. The analysis aims to determine the impact of six environmental factors on four input relaxation variables, as outlined in Table 5.

Upon conducting the significance test analysis, it was determined that environmental variables exert a noteworthy impact on the operational inputs of the sample companies. The outcomes of the Stochastic Frontier Analysis (SFA) regression indicate that the regression coefficient successfully clears the significance test at the 1% threshold. This outcome underscores the validity of excluding environmental and random interferences when constructing the SFA model. The input relaxation variable signifies the potential for enterprises to advance towards the efficiency frontier by enhancing management efficacy and optimizing resource allocation and capital operations. Should the coefficient of the input relaxation variable display a positive value, both the environment variable and the input relaxation variable align in the same direction, implying that an upsurge in environmental conditions may lead to resource mismanagement. Conversely, a negative coefficient indicates that the environmental variable plays a beneficial role in amplifying resource utilization efficiency by reducing resource inputs.

Table 5. Results of variable SFA regression analysis for sample enterprises

Items	Total carbon emissions of listed companies (tons)	Total salaries of employees	Net fixed assets	Main business costs
Constant term	0.01136	0.03449	0.00255	0.00639
Number of years since the establishment of the business	0.00170	0.03817	0.00804	0.00349
Total business assets	0.00242	0.04284	0.00039	0.01292
R&D funds	0.00039	0.01223	0.00350	0.00225
GDP per capita in the region where the enterprise is located	0.00517	0.03026	0.00746	0.00809
The proportion of transportation expenditure in the provincial region where the enterprise is located in the total local fiscal expenditure	0.00335	0.02438	0.00987	0.00263
Total route length of transport	0.00015	0.01609	0.00133	0.00411
σ^2	0.00033	0.00245	0.00405	0.00012
γ	0.93000	0.89000	1.00000	0.84000

(1) Number of years since the establishment of the business

From the data presented in the table, it is observed that there is a positive regression coefficient between the years since establishment of the enterprises and the input relaxation variables related to the total carbon emissions (tons) of listed companies. Conversely, the regression coefficients for the input relaxation variables associated with total employee salaries, net fixed assets, and main business costs demonstrate a negative relationship. The upward trend in the number of operational years could potentially result in equipment aging and an expansion of production scale, leading to a rise in total carbon emissions. On the other hand, as a company matures over time, it may become more adept at reducing labor and operational expenses, as well as making more precise investments in fixed assets.

(2) Total assets of an enterprise

Based on the information presented in the table, the regression coefficients for the total assets of enterprises and the relaxation variables associated with total carbon emissions (tons), total employee salaries, net fixed assets, and main business costs for listed companies are all positive. The escalation in total assets could signal an expansion in enterprise scale and heightened production operations, potentially necessitating increased energy consumption, employee involvement, and financial backing. Consequently, such an amplification in total assets may result in higher levels of total carbon emissions, employee salaries, and main business cost inputs.

(3) Research and development expenditure

The data in the table indicates that there are positive regression coefficients between Research and Development (R&D) expenditure and the input relaxation variables for net fixed assets, while the regression coefficients for the input relaxation variables related to total carbon emissions (tons), total employee salary, and main business cost are negative. A surge in R&D expenditure typically signifies an increased focus on research and development activities within enterprises, necessitating more production equipment and resource investments, thereby boosting net fixed assets. Furthermore, intensifying R&D efforts may steer enterprises towards fostering innovation and prioritizing environmental initiatives, consequently driving down production expenses and overall carbon emissions. Moreover, the heightened demand for skilled personnel might prompt companies to channel additional resources into hiring and training technical staff, potentially leading to a reduction in total employee salaries.

(4) GDP per capita in the region where the company is located

The regression coefficients for the per capita GDP of the region where the company is situated, total carbon emissions (tons) of listed companies, total employee salaries, net fixed assets, and the input relaxation variables for main business costs are all positive as demonstrated in the provided table. A rise in the per capita GDP of the region where the enterprise operates typically signifies an advancement in industrialization levels, potentially resulting in increased carbon emissions. Moreover, a boost in per capita GDP may necessitate higher wages from the enterprise to attract and retain skilled employees. Furthermore, the upswing in per capita GDP could attract more infrastructure investments and subsequently drive enterprise development within the region. Consequently, companies might escalate their investment in fixed assets and potentially need to enhance production scale and investments to meet market demands.

(5) The proportion of transportation expenditure in the total local fiscal expenditure of the provincial region where the enterprise is located

As per the data shown in the table, the regression coefficient for the share of transportation expenditure in the provincial region where the company is positioned within the total local financial budget, and the input relaxation variable for total employee salaries is positive. Conversely, the regression coefficients for total carbon emissions (tons), net fixed assets, and the input relaxation variable for main business costs of the listed company are negative. The escalation in the percentage of local transportation expenditure within the overall local financial budget could heighten the demand for labor within enterprises, fostering intensified competition in the labor market, thereby enhancing wage levels for employees. Nonetheless, a higher share of financial outlay in transportation implies increased regional resources allocated to transportation and transportation infrastructure development. This initiative could facilitate energy conservation and reduced transportation costs during transit, consequently curbing the enterprise's demand for transportation equipment investment and thereby lowering fixed asset expenditures.

(6) The total route length of transportation

From the data provided in the table, it is evident that the regression coefficients for the total transportation route length and the input relaxation variables for net fixed assets are negative. Conversely, the regression coefficients for the total carbon emissions (tons) of the listed company, total employee salaries, and the input relaxation variables for main business costs are positive. An increase in the transportation route length could potentially escalate transportation costs and resource depletion. This scenario might prompt enterprises to adopt measures to curtail the use of fixed assets. Nonetheless, a surge in the total transportation route length could escalate fuel consumption, vehicle operations, and labor demand. Consequently, there could be an uptick in total carbon emissions, total employee salaries, and an increased need for main business expenses to cater to the fuel requirements of long-distance transport.

5.3. The Third Stage: Analysis of Adjusted DEA Model Results

Based on the regression outcomes from the second stage, it is evident that the operational efficiency of the sample companies is influenced by six environmental factors: the establishment years of the business, total enterprise assets, Research and Development (R&D) expenditure, per capita GDP of the region where the enterprise is situated, the share of transportation spending in the province's overall local financial outlay, and the total transportation network length. To ensure result objectivity, it is essential to mitigate the influence of external environmental factors on efficiency assessments. Subsequently, the input adjustment value and the original output value derived from the Stochastic Frontier Analysis (SFA) regression analysis are utilized to reevaluate the operational efficiency of the sample companies using DEAP2.1 software.

Table 6. Comparison of the operating efficiency levels of sample companies in the first and third stages

	Comprehensive Technical efficiency		Pure technical efficiency		Scale efficiency	
	Stage One	Stage Three	Stage One	Stage Three	Stage One	Stage Three
2017	0.754	0.608	0.821	1.000	0.923	0.608
2018	0.793	0.651	0.847	1.000	0.938	0.651
2019	0.781	0.850	0.863	0.897	0.911	0.946
2020	0.831	0.947	0.88	0.967	0.947	0.979
2021	0.818	0.943	0.88	0.953	0.93	0.989
Mean value	0.796	0.800	0.858	0.963	0.930	0.835

The comparison of operational efficiency levels for the sample enterprises in the initial and third stages is displayed in Table 6. In terms of comprehensive technical efficiency, the average technical efficiency of the selected businesses exhibited a slight improvement, escalating from 0.795 in the initial stage to 0.800 over the five-year period from 2017 to 2021. The comprehensive technical efficiency value remained relatively stable pre- and post-adjustment, indicating minimal external environmental interference impacting the overall technical efficiency of the sample companies. Upon considering external environmental factors, the average pure technical efficiency of the 80 sample companies experienced a significant enhancement, surging from 0.858 initially to 0.963, marking a 10.5% increase. This surge suggests that environmental variables negatively affect the technical and managerial competence of the sample companies, underscoring an initial undervaluation of the firms' technical efficiency. Scale efficiency delineates the variance between the actual scale and the optimal production scale. After accounting for external interference, the average scale efficiency of the sample companies declined by 9.5%, from 0.930 to 0.835, signifying that numerous enterprises exhibit inefficient management resource allocation and that environmental factors aid in closing this disparity.

6. Conclusion and Suggestions

A key strategy for achieving sustainable development is low-carbon logistics. In order to support the enhancement of China's logistics enterprises' operational efficiency as well as the industry's healthy and sustainable development, this paper employs a three-stage DEA model to measure and analyze the operating efficiency of listed companies in the country's logistics sector. This article presents the following recommendations and remedies to increase the operational efficiency of China's logistics firms from the viewpoints of the government and businesses. It does this by combining the findings of empirical research with the current development scenario of the country's logistics sector.

6.1. Government Aspect

6.1.1. Provide Effective Policy Support

In the context of building a low-carbon economy, reducing carbon emissions has become one of the government's important environmental protection and economic development goals. The social economy's sustainable growth is linked to the promotion of low-carbon logistics. Within the framework of current policies, the government need to endeavor to enact further regulations that support the robust growth of the logistics sector so as to achieve a win-win situation of economic development and environmental protection. According to the results of SFA regression analysis in the second stage of this paper, it is found that the proportion of transportation expenditure in the total local financial expenditure of the province where the enterprise is located will aggravate or reduce the input factor redundancy and thus have an impact on logistics companies' operational efficiency. Therefore, when the government formulates relevant policies, it should make corresponding investments and improvements according to the current situation of transport infrastructure in different regions. Local governments should also adjust industry standards and norms in a timely manner in response to specific problems faced by the local logistics industry, so as to encourage logistics enterprises to optimize operational processes, reduce costs, and improve efficiency.

6.1.2. Promote Low-carbon Interconnected Development

At present, there are problems of resource waste and low economic efficiency in China's logistics industry. Integrating logistics resources and improving their use efficiency is the key to improving the operation efficiency of China's logistics enterprises. According to the above analysis of the status quo of logistics enterprises in our country, there are huge differences in the asset utilization efficiency and asset management ability of different companies. In view of this situation, the government can establish a logistics information sharing platform and cooperation mechanism to promote cooperation and exchange among logistics enterprises, jointly solve the problems of carbon emissions and environmental protection, and improve overall logistics efficiency. In addition, in order to really bring about the industry's low-carbon and green transition, the government can promote the implementation of green supply chain management by logistics enterprises, encourage enterprises to cooperate with suppliers, customers, and partners to jointly reduce carbon emissions, save energy and resources, and promote the low-carbon interconnected development of the industry.

6.2. Corporate Aspects

6.2.1. Allocate Resources Properly

According to the empirical analysis results in Chapter 4, the pure technical efficiency of the third stage has been greatly improved compared with that of the first stage, which means that after considering the environmental variables and input relaxation variables, China's logistics enterprises have realized more efficient resource utilization. Resource input is a prerequisite for the operation of logistics enterprises. Ineffective input will not only have an impact on businesses' manufacturing efficiency but also lead to resource waste and environmental pollution. Therefore, a reasonable allocation of resource input is crucial. In order to carry out effective resource allocation, logistics enterprises must identify the reasons leading to the redundancy of input factors and the existing problems in output and adjust and optimize them. Taking the total carbon emissions of listed companies as a factor in energy consumption, short-term carbon emission data does not represent the realization of the long-term green development of the enterprise. It is necessary to regularly monitor and update the total carbon emission data of listed companies, track the change in energy consumption level of logistics enterprises, and timely discover the change in energy consumption trend so as to provide references for enterprises to formulate effective resource management, energy-saving techniques and methods for reducing emissions. Faced with the unreasonable allocation of resources, China's logistics enterprises should reasonably adjust the allocation of resources to ensure that fixed assets, total carbon emissions, and other inputs match the actual scale and demand of enterprises.

6.2.2. Improve Technology and Staff Training

According to the empirical results in Chapter 4, the pure technical efficiency of the third stage is higher than that of the first stage, indicating that the enterprise can still improve its pure technical efficiency under the control of environmental variables and random factors, indicating that the enterprise still has some potential room for improvement and needs to take some measures to improve the operation efficiency. On the one hand, Logistics companies must continually innovate and grow in order to fulfill market demands against the backdrop of a low-carbon economy. Therefore, China's logistics enterprises can learn from the advanced management mode of foreign logistics enterprises, introduce new green production technology, improve production efficiency, and reduce production costs by optimizing production processes and supply chain management. On the other hand, with the increasing environmental requirements of customers for logistics enterprises, employees need to have the knowledge and skills that are also increasing. In this regard, listed companies in China's logistics industry can implement staff training and incentive programs through regular training and incentive mechanisms to encourage workers' passion and inventiveness to raise the standard of quality and production efficiency in businesses.

6.2.3. Reasonable Reduction of Production Scale

According to the empirical analysis results in Chapter 4, most of the 80 sample companies have a certain uneconomy or underutilization of scale, which leaves a large room for improvement. In the third stage of eliminating environmental factors, most of the sample companies are in a state of diminishing returns to scale, and they need to reduce production scale to improve operational efficiency. However, blindly reducing the production scale may bring certain risks to the operation efficiency of enterprises. Therefore, logistics enterprises need to adjust the scale in a timely manner, optimize the operation according to their own situation and market demand, and comprehensively consider factors such as resource allocation and management level to increase both the overall operating efficiency and scale efficiency. Specific measures include: first, enterprises need to review the internal resource allocation, including manpower, capital, materials, etc., to ensure that they can make full use of and maximize the value; second, strengthen the management and operation of enterprises by introducing advanced management methods and technologies to optimize processes, reduce waste, and improve efficiency; and finally, establish a mechanism and culture of continuous improvement to enable enterprises to stay within the optimal production scale range through continuous optimization and adjustment, so as to achieve long-term stable and efficient operations.

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