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Analysis of Logistics Efficiency Measurement and Influencing Factors in Anhui Province from the "Double Carbon" Perspective

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ABSTRACT

With the proposal of the "Double Carbon" goals, the work of carbon peaking and carbon neutrality has been comprehensively promoted. How to improve, logistics efficiency while achieving low-carbon development in the logistics industry has become an urgent issue to address. This study takes 16 prefecture-level cities in Anhui Province as decision-making units, constructs an efficiency evaluation index system, and uses the three-stage DEA model and Malmquist index model to measure the static and dynamic efficiency of the logistics industry in Anhui Province. The Tobit model is then employed to analyze the factors in social life that influence the development of the logistics industry. Finally, reasonable and effective countermeasures and suggestions are formed. The research aims to enhance the overall level of logistics in Anhui Province, provide options for industrial pathways for logistics development under the low-carbon background, and achieve high-quality development.

KEYWORDS

Logistics industry efficiency; Carbon emissions; Three-stage DEA; Malmquist index model; Tobit

1. INTRODUCTION

With the increasing global focus on climate change, the goals of carbon peaking [1] and carbon neutrality have become critical tasks for national development. As the world's largest developing country, China has actively responded to climate change by proposing the "Double Carbon" goals, aiming to achieve carbon peaking before 2030 and carbon neutrality before 2060. These goals have set higher requirements for the low-carbon development of all industries. As a key supporting industry of the national economy, the low-carbon transformation and efficiency improvement of the logistics industry have become urgent issues to address.

As an important province in central China and a key node in the Yangtze River Economic Belt and the Yangtze River Delta Integration Development, Anhui Province's logistics industry plays a vital role in regional economic development. However, while the logistics industry in Anhui has grown rapidly, it faces challenges such as low resource utilization efficiency and high carbon emissions. Under the constraints of the "Double Carbon" goals, improving the efficiency of Anhui's logistics industry and achieving low-carbon development is not only an important theoretical research topic but also an urgent practical need. This paper aims to construct a scientific and reasonable evaluation index system, use the three-stage DEA [2] model and Malmquist index model [3] to measure the static and dynamic efficiency of the logistics industry in Anhui Province, analyze the social factors influencing logistics development using the Tobit model [4], and provide theoretical support and policy recommendations for the high-quality development of Anhui's logistics industry.

2. RESEARCH METHODS AND DATA SOURCES

2.1. Research Methods

(1) The core idea of the three-stage DEA method is as follows:

First stage: Use the unmodified DEA model to calculate the initial data to obtain efficiency values and input differences for each sample enterprise.

Second stage: Employ the difference values and selected environmental variables to correct the inputs of enterprises in the sample through the Stochastic Frontier Analysis (SFA) model [5], eliminating environmental influences and error factors.

Third stage: Replace the input elements with the corrected data in the DEA model again; the resulting values at this stage represent the net management efficiency values unaffected by environmental factors and random disturbances.

In the first stage of calculating initial efficiency, assuming input dominance and considering the many uncontrollable scenarios in enterprise production, the BCC model [6] is used to measure the efficiency of regional production activities. The model is as follows:

$$\min\theta = V_{D2}$$
$$BC^2 \begin{cases} \sum_{j=1}^{n} X_j\lambda_j + S^- = \theta X_0, \\ \sum_{j=1}^{n} Y_j\lambda_j - S^+ = Y_0, \\ \sum_{j=1}^{n}\lambda_j = 1 \\ \lambda_j \geq 0, j = 1,2,,,n \end{cases} \tag{1}$$

In the second stage, the core task is to eliminate external factors, random disturbances, and factors causing management inefficiency to ensure the accuracy of the evaluation. Through this process, we can obtain the input values of each region under the same environmental conditions.

$$X_{ni}^{A} = X_{ni} + [MAX_i\{\beta^n Z_i\} - \beta^n Z_i] + [MAX_i\{v_{ni}\} - v_{ni}], n = 1,2,,N, i = 1,2,,I \tag{2}$$

The selected input X and output indicator Y are both designed to reflect the value creation process of the logistics industry, representing n activity samples. θ can reflect the logistics efficiency level of each region after adjustment and optimization in key aspects such as factor integration and operational management. With the constructed measurement model, it is not only possible to accurately calculate the corresponding logistics efficiency values of TE, PTE, SE, but also to further derive the input target values of each activity sample, and then calculate the slack variables, providing an important basis for subsequent efficiency improvement analysis.

Among them, X_{ni}^{A} represents the adjusted input value, while X_{ni} is the initial input value before adjustment. The two parentheses respectively denote the processing of all decision-making units to eliminate the impacts of environmental factors and random errors, thus placing them on a unified comparison benchmark and ensuring they are free from interference by other external factors.

In the third stage, DEA measurement is performed on the adjusted inputs. At this stage, we conduct an in-depth analysis of the adjusted efficiency. The BCC model is applied again for efficiency measurement. We retain the original status of the output data, while the input data use the adjusted values that have excluded the influence of other external factors, putting all decision-making units on the same level. More accurate efficiency values can be calculated, which are no longer disturbed by external factors, thereby providing a more reliable data foundation for subsequent analysis.

(2) Malmquist Index Method

The Malmquist Index was originally designed to measure the dynamic changes in Total Factor Productivity (TFP). By decomposing TFP, the Malmquist Index can reveal the changing trends of technological progress and technical efficiency, where technical efficiency can be further broken down into pure technical efficiency and scale efficiency. Therefore, this paper uses the Malmquist Index model to evaluate the dynamic performance of logistics efficiency in Anhui Province.

Here, $D^t(X^t, Y^t)$ denotes the distance function between the production efficiency of the activity object in period t and the optimal production frontier in period t. To separately extract technical efficiency (effch) and technological progress (techch) [7] from the above index, we performed a formula decomposition on the index, leading to the following equations:

$$M(X^{t+1}, Y^{t+1}, X^t, Y^t) = \frac{D^t(X^t, Y^t)}{D^{t+1}(X^{t+1}, Y^{t+1})} \times \left[\frac{D^{t+1}(X^t, Y^t)}{D^t(X^t, Y^t)} \times \frac{D^{t+1}(X^{t+1}, Y^{t+1})}{D^t(X^{t+1}, Y^{t+1})}\right]^{\frac{1}{2}} = \mathrm{eff}ch \times \mathrm{te}chch \tag{3}$$

(3) Tobit Model

Combining the research achievements of existing scholars, this paper decides to use the Tobit model to explore the main factors influencing logistics efficiency. The Tobit model is particularly suitable for analyzing data where the dependent variable is truncated or undergoes truncation during data collation and is correlated with independent variables. Therefore, this paper selects the Tobit model for parameter estimation of influencing factors to more accurately identify and quantify the key driving factors affecting logistics efficiency in Anhui Province.

The basic form of the Tobit model can be expressed as:

$$\begin{aligned} y_i &= \beta^T X_i + \varepsilon_i, \beta^T X_i + \varepsilon_i > 0 \\ y_i &= 0, \beta^T X_i + \varepsilon_i \le 0 \end{aligned} \tag{4}$$

The linear regression model is constructed as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7 + \varepsilon \tag{5}$$

2.2. Data Sources

The research object of this paper is the 16 prefecture - level cities in Anhui Province. As mentioned before, there is currently no specialized data statistics for the logistics industry in China. Therefore, when collecting data, this paper uses the data of "transportation, warehousing and postal services" in the statistical yearbooks to replace the data of the logistics industry. The data are sourced from China Statistical Yearbook and China Energy Statistical Yearbook from 2016 to 2020.

3. EMPIRICAL ANALYSIS

3.1. First Stage

Relevant logistics data of 16 cities in Anhui Province from 2011 to 2020 were selected and input into the DEAP2.1 software. The BCC-DEA model was used to calculate the comprehensive technical efficiency [8] as specifically shown in Table 1. Subsequent analysis was conducted based on the results.

Table 1. Comprehensive technical efficiency and ranking in the first stage of 2011-2020

DMU	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean Value	Ranking
Hefei	1	1	1	1	1	1	1	1	1	1	1	1
Huaibei	0.935	0.965	1	1	1	1	1	1	1	1	0.990	2
Bozhou	1	1	1	1	1	1	1	1	1	1	1	1
Suzhou	0.97	1	1	1	0.7	0.812	0.91	1	1	1	0.939	7
Bengbu	0.953	0.997	0.932	1	1	1	1	1	1	1	0.988	3
Fuyang	1	1	1	1	1	1	1	1	1	1	1	1
Huainan	0.692	1	0.909	0.941	0.962	1	1	1	0.962	0.859	0.933	9
Chuzhou	0.704	0.684	1	1	1	1	1	0.877	0.841	0.675	0.878	12
Liuan	1	1	1	1	0.714	0.923	1	1	1	1	0.964	4
Ma'anshan	0.837	1	1	0.822	0.901	0.965	1	0.877	0.731	0.824	0.896	11
Wuhu	0.877	0.816	0.917	0.982	0.958	0.955	0.951	0.948	0.793	0.962	0.916	10
Xuancheng	0.766	0.825	1	1	1	1	1	1	1	1	0.959	5
Tongling	1	1	1	1	1	1	1	1	1	1	1	1
Chizhou	1	0.699	0.692	0.826	0.805	0.832	0.844	0.774	0.693	0.61	0.778	13
Anqing	1	1	1	0.798	0.939	0.832	0.788	1	1	1	0.936	8
Huangshan	1	1	1	1	1	1	1	1	0.765	0.744	0.951	6

Comprehensive technical efficiency reflects the production efficiency of decision-making units (DMUs) under given (optimal scale) input factor conditions, and can be used to measure and evaluate the resource utilization efficiency, effectiveness, and resource allocation capabilities and status of DMUs. Table 1 presents the comprehensive technical efficiency, average values, and rankings of the logistics industry in various regions of Anhui Province from 2011 to 2020.

Among the regions in Anhui Province, four cities—Hefei, Bozhou, Fuyang, and Tongling—achieved a comprehensive technical efficiency score of 1 in logistics from 2011 to 2020, indicating that their logistics efficiency reached the DEA-effective level. Among the remaining cities, nine cities—Huaibei, Suzhou, Bengbu, Huainan, Liuan, Wuhu, Xuancheng, Anqing, and Huangshan—had average comprehensive technical efficiency values in logistics between 0.9 and 1, falling on the margin of DEA inefficiency and classified as DEA weakly effective. Three cities—Ma'anshan, Chuzhou, and Chizhou—had average comprehensive technical efficiency values in logistics below 0.9, specifically 0.896, 0.878, and 0.778, respectively, and were classified as DEA inefficient. Among the 16 cities, Chizhou had the lowest average comprehensive technical efficiency in logistics at 0.778, showing a significant gap from reaching the DEA-effective level.

3.2. Third Stage

Table 2. Comprehensive technical efficiency and ranking of the third stage in 2011-2020

DMU	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Mean Value	Ranking
Hefei	1	1	1	1	1	1	1	1	1	1	1	1
Huaibei	0.87	0.854	1	1	1	1	1	1	1	1	0.9724	5
Bozhou	1	1	1	1	1	1	1	1	1	1	1	2
Suzhou	1	1	1	1	0.761	0.856	0.946	1	0.977	1	0.954	10
Bengbu	0.885	0.926	0.877	0.914	1	1	1	1	1	1	0.9602	9
Fuyang	1	1	1	1	1	1	1	1	1	1	1	3
Huainan	0.526	0.56	0.671	0.933	0.985	1	1	1	0.97	0.948	0.8593	15
Chuzhou	0.84	0.85	1	1	1	1	1	0.911	0.908	0.835	0.9344	12
Liuan	1	1	1	1	0.807	0.964	1	1	1	1	0.9771	4
Ma'anshan	0.992	1	0.992	0.873	0.961	0.991	1	0.955	0.779	0.869	0.9412	11
Wuhu	0.859	0.887	0.941	0.974	0.993	0.994	0.987	0.97	0.789	0.872	0.9266	13
Xuancheng	0.832	0.892	1	1	1	1	1	1	1	1	0.9724	6
Tongling	1	1	1	1	1	1	1	1	0.869	0.854	0.9723	7
Chizhou	0.715	0.596	0.64	0.703	0.712	0.729	0.748	0.703	0.628	0.628	0.6802	16
Anqing	1	1	1	0.842	0.978	0.928	0.915	1	1	1	0.9663	8
Huangshan	0.938	0.767	0.814	1	1	1	1	1	0.567	0.563	0.8649	14

According to the data in Table 2, among the 16 cities in Anhui Province, Hefei, Bozhou, and Fuyang ranked first with an average comprehensive technical efficiency score of 1 from 2011 to 2020, indicating that their logistics comprehensive technical efficiency reached the DEA-effective level. Nine cities, including Huaibei, Suzhou, Bengbu, Chuzhou, Ma'anshan, Wuhu, Xuancheng, Tongling, and Anqing, had average comprehensive technical efficiency values between 0.9 and 1, classified as DEA weakly effective. However, three cities—Huainan, Chizhou, and Huangshan—had average comprehensive technical efficiency values below 0.9. Notably, Chizhou had the lowest average score at 0.6802, showing a significant gap from the DEA-effective level. Therefore, it is necessary to conduct an in-depth analysis of the reasons for Chizhou's low comprehensive technical efficiency to provide a clear direction for the development of its logistics industry.

3.3. Comparative Analysis Between the First and Third Stages

(1) Overall Analysis

When evaluating Anhui Province as a whole, the first stage of the three-stage DEA analysis indicates that the logistics efficiency of four cities—Hefei, Bozhou, Fuyang, and Tongling—achieved DEA effectiveness. However, after the second-stage SFA regression analysis and data adjustment, only three cities (Hefei, Bozhou, and Fuyang) maintained DEA-effective logistics efficiency, while Tongling's efficiency shifted to DEA weak effectiveness. Meanwhile, the logistics efficiency values of the other 12 cities exhibited varying degrees of increase or decrease. This highlights the necessity of using SFA regression analysis to eliminate the influence of environmental factors and random errors in logistics efficiency evaluation.

(2) Regional Analysis

To visually illustrate the impact of environmental factors and random errors on the efficiency values of Anhui's 16 cities during 2011–2020 in the first and third stages, a radar chart was plotted.

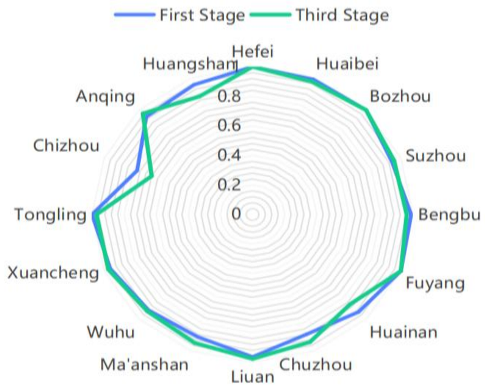

Figure 1. Impacts on Efficiency Values of 16 Cities in the First and Third Stages

As can be seen from the figure, during the period of 2011-2020, the comprehensive logistics efficiency values of Hefei, Bozhou, and Fuyang remained DEA-effective in both the first and third stages. This indicates that the logistics industry development in these cities is relatively stable and less susceptible to environmental factors and random factors. After SFA regression adjustment, however, the logistics efficiency of Tongling dropped from DEA-effective to the edge of near DEA-ineffectiveness, mainly due to the decline in scale efficiency after the third-stage adjustment, which shows that scale efficiency has a significant impact on Tongling's logistics efficiency.

3.4. Analysis Results of Influencing Factors

As the research data in this paper are all panel data, Stata16.0 software was used for Tobit regression, and the regression results of the influencing factors of China's logistics efficiency under the "double carbon" background are obtained, as shown in Table 3:

Table 3. Empirical Analysis Results of Influencing Factors of China's Logistics Efficiency

Independent Variable	Regression Coefficient
X1	0.0990**(0.0478)
X2	0.0640**(0.0271)
X3	0.410***(0.0697)
X4	0. 149*(0.0766)
X5	-0.00398**(0.00160)
X6	0. 165***(0.0429)
X7	0.00147(0.00777)

As mentioned above, six factors influence logistics efficiency, including economic development level and human resource level. Among them, economic development level, human resource level, locational advantage, degree of openness, and energy utilization rate have a positive impact.

The regression coefficient of economic development level is 0.0990, reflecting its close connection with the development of the logistics industry.

The impact coefficient of human resource level is 0.0640, indicating its role remains insignificant under the "double carbon" background.

The regression coefficient of locational advantage is 0.410, demonstrating a significant impact on the development of the logistics industry.

The regression coefficient of the degree of openness is 0.149, which can promote technological innovation and talent flow.

The regression coefficient of energy utilization rate is 0.165, which can facilitate the rational use of resources.

In addition, informatization level has a negative effect on logistics efficiency: a 1-unit increase in informatization leads to a 0.00398 decrease in logistics efficiency. This may be due to differences in research methods, insufficient technical talent, and lagging infrastructure. Although government intervention has a positive impact, it has not significantly promoted the improvement of logistics efficiency due to lax environmental pollution control. In the future, strict environmental protection measures and the introduction of refined policies can be adopted to promote such improvement.

4. CONCLUSIONS AND POLICY RECOMMENDATIONS

This chapter conducts an empirical analysis of logistics efficiency in various regions of Anhui Province using the three-stage DEA model and Malmquist Index method, constituting the core part of this study. The three-stage DEA model is employed to eliminate the interference of external environments and random errors, addressing the limitations of traditional DEA models. The analysis reveals that although the efficiency of the logistics industry in Anhui Province shows an upward trend, the overall level remains low, with significant regional disparities. External environmental factors have a substantial impact on logistics efficiency. Overall, the comprehensive technical efficiency (TE) of Anhui's logistics industry is far lower than pure technical efficiency (PTE) and scale efficiency (SE), indicating that technological capabilities and scale limitations are major constraints on its development.

Given that the three-stage DEA model can only analyze logistics efficiency from a horizontal perspective, this chapter further uses the Malmquist Index method for vertical analysis and compares results before and after excluding external environments and random errors. The analysis finds that the productivity index decreases due to the influence of the technological progress index, while the technical efficiency change index fluctuates slightly. Compared with total factor productivity before input adjustment, the productivity index after adjustment fluctuates more gently and generally shows a growth trend.

Based on the above findings, this paper proposes the following policy recommendations:

Accelerate the construction and layout of logistics network node infrastructure: Increase investment in logistics infrastructure, optimize logistics network layout, and improve the utilization efficiency of logistics resources. In particular, economically underdeveloped regions should strengthen logistics infrastructure construction to narrow regional gaps.

Promote logistics technological innovation and informatization: Encourage logistics enterprises to increase investment in technological innovation, promote advanced logistics technologies and management methods, and improve the intelligence level of logistics services. Meanwhile, advance logistics informatization to enhance the sharing and utilization efficiency of logistics information.

Optimize industrial structure and develop a low-carbon economy: Accelerate industrial restructuring, eliminate high-energy-consuming and high-polluting enterprises, and develop low-carbon and high-tech industries. Introduce advanced energy-saving equipment and technologies to promote industrial restructuring and upgrading, and foster green economic development models.

Strengthen government macro-control and optimize the policy environment: The government should introduce and implement relevant laws and regulations, incorporating "green logistics" into long-term government planning. Implement clean energy tax subsidies and carbon emission trading systems, accelerate the application of green technologies and waste recycling technologies, address high-energy consumption and pollution issues, and achieve sustainable development.

Through these policy recommendations, this study aims to provide theoretical support and practical guidance for the low-carbon development of Anhui's logistics industry under the "double carbon" goals, and promote the high-quality development of the logistics industry in Anhui Province.

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