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AN EMPIRICAL STUDY ON ENVIRONMENTAL EFFICIENCY MEASUREMENTS AND INFLUENCING FACTORS

Abstract: Airlines are an important part of the comprehensive transportation system. Therefore, it is of great practical significance to empirically analyse the measurement of airlines' environmental efficiency and influencing factors. Adopting the SBM-DEA model, this study measured the environmental efficiency of 20 Chinese airlines between 2010 and 2017 and empirically analysed the factors influencing their environmental efficiency using a Tobit regression model. Spring Airlines, China Southern Airlines, and Hainan Airlines were found to have the highest environmental efficiency. Tianjin Airlines, Hebei Airlines, and China Express Airlines had the lowest environmental efficiency. The Tobit regression results showed that average flight distance, load factor, market share, and proportion of cargo and mail turnover had a significant positive effect on airline environmental efficiency. Fuel consumption per ton-km had a significant negative effect on airline environmental efficiency.

Keywords: environmental efficiency, SBM-DEA model, Tobit regression, sustainability, sustainable environment

Introduction

Since China's reform and opening up, the country's civil aviation industry has shown a rapid growth trend. Over the past 40 years, from 1978 to present, the average annual growth rate of China's civil aviation transportation turnover reached 16.18 %. Moreover, since 2005, the total turnover of civil air transportation in China has ranked second in the world for 14 consecutive years. Consequently, the consumption of aviation kerosene has increased dramatically, and the resulting carbon dioxide emissions have also increased significantly. In the past two decades, however, in the context of global responses to climate change, the International Civil Aviation Organization (ICAO) has promoted reducing aviation emissions. Accordingly, increased environmental constraints have been placed on civil aviation industry development.

Meanwhile, in the context of China's rapid development, environmental issues have become increasingly prominent, placing pressure on the development of various domestic industries. However, in China's civil aviation industry, energy conservation and emission-reduction efforts still face problems such as weak foundations, insufficient

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technology accumulation, and rudimentary operational management. Carbon emissions from China's airlines account for approximately 95 % of the carbon emissions of the civil aviation industry. Therefore, effectively controlling airline carbon emissions and promoting low-carbon transportation capacity have become high priorities in the civil aviation industry.

Airline environmental efficiency is defined as the production efficiency of carbon emissions containing undesired outputs, which can fully reflect the conversion relationship between all input factors and expected output and undesired output in the airline production system [1-3]. Airline environmental efficiency is an important measure of an airline's low-carbon transportation capacity. Therefore, to achieve green development and reduce constraints on the aviation industry, it is necessary to accurately measure airlines' environmental efficiency, find the important constraints affecting airlines' low-carbon transportation capacity, and propose relevant improvement measures and effective programs [4-6].

Literature review

Identifying environmental efficiency is key to studying environmental efficiency issues. In terms of measurement methods, data envelopment analysis (DEA) is the commonly used tool for measuring environmental efficiency [7], and its various models are widely used in environmental efficiency measurement research [8-10]. While there are few empirical studies of the environmental efficiency of civil aviation in China, there is an abundance of related literature abroad. The research methods can be divided into two categories. In the first category, a traditional DEA model is used to study the environmental efficiency of airlines. Zou et al. [11] used a DEA model to measure the fuel efficiency of 15 US airlines in 2010. Transportation distance and the number of passenger miles were shown to have a significant effect on fuel efficiency. In the second category, an slack based measure (SBM-DEA) model is used to study the environmental efficiency of airlines. Tone [12] developed an SBM-DEA model to measure environmental efficiency in 2003, which has since been adopted by other scholars. Cui and Li [13] used a network SBM-DEA model with weak disposability to measure the energy efficiency of 22 international airlines in the operational and carbon-emission-reduction phases from 2008 to 2012. The results indicated that European airlines had the highest energy efficiency levels among the airlines being measured. Chang et al. [14] measured the economic and environmental efficiency of 27 global airlines in 2010 using an SBM-DEA model. Those results indicated that Asian airlines were the most efficient, followed by European and American airlines.

In summary, while there has been progress in research on airline environmental efficiency, further exploration is still needed. First, there are few empirical studies on the factors influencing the environmental efficiency of Chinese airlines. Second, there are clear drawbacks in the selection of input-output indicators. In the past, studies selected the number of aircrafts as the input indicator; this ignored the large differences between different models and thus could not accurately reflect the actual input of airline capacity. As a result, there is no guarantee of the accuracy of environmental efficiency measurement results. In light of this, the present study used an SBM-DEA model to measure the environmental efficiency of airlines. Based on the measurement results for environmental efficiency, a Tobit regression model was used to empirically analyse the factors influencing the environmental efficiency of airlines. Based on the findings of this study, targeted

improvements and program recommendations are proposed to improve the environmental efficiency of China's airlines.

Methodology and data

First, an SBM-DEA model was constructed to measure the environmental efficiency of 20 representative domestic airlines in China from 2010 to 2017. Then, a Tobit regression model was used to explore the influencing factors of airline environmental efficiency based on environmental efficiency measures.

Environmental efficiency measurement model

SBM-DEA model

An SBM-DEA model can effectively avoid the measurement deviation caused by angle selection and radial selection. This model can also introduce the slack variable into the objective function, excluding the influence of nonefficiency factors. Therefore, the proposed model, which is somewhat different from previous models, can fully reflect the essence of environmental efficiency measurements [10]. Drawing on Tone's [12] approach, this study established the basic form of an SBM-DEA airline environmental efficiency measurement model with types of inputs, types of expected outputs, and types of undesired outputs of, as follows:

$$\min h_0 = \frac{1 - \frac{1}{m} \left(\sum_{i=1}^m \frac{s_i^x}{x_{i0}} \right)}{1 + \frac{1}{s+k} \left(\sum_{r=1}^s \frac{s_r^y}{y_{r0}} + \sum_{p=1}^k \frac{s_p^z}{z_{p0}} \right)} \quad (1)$$

$$\sum_{j=1}^n \lambda_j x_{ij} + s_i^x = x_{i0}, \forall i; i = 1, 2, \dots, m; s_i^x \geq 0; \quad (2)$$

$$\sum_{j=1}^n \lambda_j y_{rj} - s_r^y = y_{r0}, \forall r; r = 1, 2, \dots, s; s_r^y \geq 0; \quad (3)$$

$$\sum_{j=1}^n \lambda_j z_{pj} + s_p^z = z_{p0}, \forall p; p = 1, 2, \dots, k; s_p^z \geq 0; \quad (4)$$

$$\lambda_j \geq 0, \forall j, j = 1, 2, \dots, n; \quad (5)$$

The above model is an SBM-DEA model under the assumption of constant returns to scale, with s_i^x , s_r^y , s_p^z representing the slack variables of the inputs and outputs. When $s_i^x = s_r^y = s_p^z = 0$, there is no redundancy in the input, no shortage of expected output, no redundancy in the undesired output, and no room for adjustment in the input and output. The optimal solution of the model is $h_0 = 1$, indicating that the decision-making unit does not have efficiency loss; that is, the decision unit's environmental efficiency level SBM-DEA is valid. When any slack variable from s_i^x , s_r^y , s_p^z is not zero, then $0 < h_0 < 1$.

In other words, the decision unit has efficiency loss; that is, the decision unit's environmental efficiency level SBM-DEA is invalid.

Input-output indicators and data sources

Thus far, the selection of airline input and output indicators has not been finalized [15]. Based on the production characteristics of airlines, this study improved upon Zhao's [16] input and output indicators. For this study, available ton-km (ton = Mg = 10^6 g) and aviation kerosene consumption were selected as input indicators. Airline passenger turnover and cargo-mail turnover were the expected output indicators, and an airline's carbon emissions was the undesired output indicator.

1. Input indicators

Available ton-km: This indicator - the product of the number of an airline's available seats and the total route mileage in a specific period - can accurately express the actual capacity input of an airline.

Aviation kerosene consumption: Aviation kerosene consumption accounts for more than 90 % of the energy input. Therefore, airlines' energy input is expressed by aviation kerosene consumption.

2. Expected output indicators

Passenger/cargo-mail turnover: This indicator refers to the product of the passenger/shipment weight an airline actually transports and the transport distance in a specific period. These are important indicators for measuring an airline's production capacity. Therefore, this study selected passenger/cargo-mail turnover as the expected output indicator.

3. Undesired output indicators

Carbon emissions: The carbon dioxide emitted by airlines burning aviation kerosene is the most important greenhouse gas and an important source of global warming. Therefore, carbon emissions were selected as the indicator for undesired output.

This study did not consider pure cargo airlines. In consideration of data availability, data were selected from 20 representative domestic airlines from 2010 to 2017. The transportation turnover of these 20 airlines accounts for approximately 80 % of China's total civil aviation; thus, their environmental efficiency status is representative of the industry. These airlines include the following: China International Airlines, Eastern Airlines, China Southern Airlines, Hainan Airlines, Sichuan Airlines, Chengdu Airlines, Shandong Airlines, Hebei Airlines, Spring Airlines, Shanghai Juneyao Air, Okay Airways, China Express Airlines, Shanghai Airlines, Tianjin Aviation, Shenzhen Airlines, Capital Airlines, Chongqing Airlines, Kunming Airlines, Changan Airlines, and Yunnan Lucky Air. The data came from the China Civil Aviation Statistical Yearbook and the annual reports of some of the listed airlines.

Tobit regression model

To further explore the factors influencing airline environmental efficiency, regression analysis was conducted based on the environmental efficiency values measured by the SBM-DEA model. Because the environmental efficiency value measured by the SBM-DEA model is used as the explanatory variable - and the size is between 0 and 1 and is a continuous restricted variable with nonnegative value and fragmentation - it makes sense to adopt a Tobit model that follows maximum likelihood estimation [17]. The standard formula for the model is:

$$y_i^* = x_i \beta + \varepsilon_i; \varepsilon_i \sim N(0, \delta^2) \quad (6)$$

$$y_i = \begin{cases} y_i^* & y_i^* \geq 0 \\ 0 & y_i^* < 0 \end{cases} \quad (7)$$

where x_i is an explanatory variable, y_i^* is a latent variable, β represents the estimated parameters, ε_i represents the random error terms, and the distribution is normal. When the latent variable $y_i^* \geq 0$, y_i represents actual observations. When the latent variable $y_i^* < 0$, y_i is 0.

Variable selection and impact prediction

This study aimed to determine the factors that influence environmental efficiency in terms of airline carbon emissions. An airline's carbon emissions can be expressed as follows:

$$C = \beta \cdot E_f \cdot RTK \quad (8)$$

where C represents the airline's carbon dioxide emissions, β represents the conversion factor of standard coal converted to aviation kerosene, E_f represents the airline's fuel consumption per ton-km, and RTK represents the total transportation turnover of the airline, calculated in units of ton-km, as shown in the following equation:

$$RTK = \sum (L \cdot LD) \approx \sum (L_{\max} \cdot LD_a \cdot Z) \quad (9)$$

where L denotes the transportation volume of passengers, cargo, and mail in a certain segment, calculated in [ton], and LD denotes the distance of the corresponding flight segment. $L_{\max}$ denotes the maximum carrying capacity of a certain flight segment, Z denotes the load factor, and LD_a denotes the average flight distance. Formula (10) can be obtained by synthesizing formulas (8) and (9) as follows:

$$C \approx \beta \cdot E_f \sum (L_{\max} \cdot LD_a \cdot Z) \quad (10)$$

Based on the calculation of airline carbon emissions using formula (9), the conversion factor β for converting aviation kerosene to standard coal cannot be changed within a specific period, and the maximum carrying capacity $L_{\max}$ of a certain flight segment is excluded. Airline carbon emissions are mainly affected by average flight distance, load factor, and fuel consumption per ton-km. Therefore, average flight distance, load factor, and fuel consumption per ton-km were selected as the core explanatory variables to empirically study the factors influencing airlines' environmental efficiency. Based on prior literature, the proportion of cargo and mail turnover and market share were selected as control variables. The higher the proportion of cargo and mail turnover, the higher the operational efficiency of the airline, which in turn helps improve environmental efficiency [18-20]. Market share embodies the scale of airline production, which has some effect on improving an airline's environmental efficiency [21-25]. It is necessary, therefore, to control the impact of the proportion of cargo and mail turnover and market share on airline environmental efficiency. Table 1 lists the variable definitions and impact predictions [26-29].

Table 1

Variable definitions and impact predictions

Statistical variable	Variable name	Variable symbol	Definition and unit	Impact prediction
Dependent variable	Environmental efficiency	EFF	Environmental efficiency value	
Core explanatory variables	Average flight distance	Ld_a	Route total mileage/number of routes	Positive
	Load factor	Z	Actual transport ton-km/airline available ton-km	Positive
	Fuel consumption per ton-km	E_f	Total enterprise jet fuel consumption/enterprise total transportation turnover	Negative
Control variables	Market share	S	Total transportation volume of the enterprise/total transportation turnover of the whole industry	Positive
	Proportion of cargo and mail turnover	H	Cargo and mail turnover/total turnover	Positive

Now, the Tobit regression model is shown as:

$$y_{it}^* = EFF_{it} = \alpha + \beta_1 LD_{a_{it}} + \beta_2 Z_{it} + \beta_3 E_{f_{it}} + \beta_4 S_{it} + \beta_5 H_{it} + \varepsilon_{it} \quad (11)$$

where y_{it}^* denotes the environmental efficiency value of i airline in year t , α is the undetermined coefficient, and ε_{it} is the system error. Table 2 presents the descriptive statistics for the variables.

Table 2

Descriptive statistics of the variables

Variable name	Sample number	Minimum value	Maximum value	Average	Standard deviation
EFF	160	0.12	1.00	0.78	0.22
Ld_a	160	621.92	1922.72	1280.42	275.76
Z	160	63.70	98.00	76.70	7.34
E_f	160	2.41	6.78	3.38	0.72
H	160	0.01	0.55	0.11	0.08
S	160	0.00	0.21	0.04	0.06

The data came from the *China Civil Aviation Statistical Yearbook* and the *Official Aviation Guide OAG*

Empirical results

Airline environmental efficiency measurement results and analysis

MATLAB R2017a was used to run the SBM-DEA model to calculate the environmental efficiency values of 20 airlines for 2010-2017. Table 3 shows the specific calculation results.

Based on the averages of environmental efficiency during the study period, the 20 selected airlines were divided into three echelons. The first echelon had the highest environmental efficiency, followed by the second echelon. The third echelon had relatively low environmental efficiency. The first-echelon airlines included Spring Airlines, China Southern Airlines, Hainan Airlines, International Airlines, Shenzhen Airlines, Changan Airlines, and Eastern Airlines. The average environmental efficiency of the first-echelon

airlines was greater than 0.9, suggesting that the growth of airline transportation turnover in the first echelon has been well coordinated with carbon emissions. It is noteworthy that the environmental efficiency of the low-cost Spring Airlines reached the valid SBM-DEA level for eight consecutive years, indicating ongoing optimal production. The second-echelon airlines included Okay Airways, Sichuan Airlines, Shandong Airlines, Shanghai Airlines, Kunming Airlines, Yunnan Lucky Air, Capital Airlines, and Juneyao Airlines. The average environmental efficiency of the second-echelon airlines fell between 0.7 and 0.9, suggesting that the growth of airline transportation turnover in the second echelon has been comparatively coordinated with carbon emissions, although there is room for environmental improvement. The third-echelon airlines included Chongqing Airlines, Tianjin Airlines, Hebei Airlines, and China Express Airlines. The average environmental efficiency of the third echelon's airlines was less than 0.7, suggesting that the growth of airline transportation turnover in that echelon has not been coordinated with carbon emissions. There is significant room for improvement in environmental efficiency, which plays a prominent role in carbon emission reduction.

Table 3

Airline environmental efficiency values, 2010-2017

Enterprise	2010	2011	2012	2013	2014	2015	2016	2017	Average
Spring Airlines	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.000
China Southern Airlines	1.00	1.00	1.00	1.00	0.99	1.00	1.00	1.00	0.999
Hainan Airlines	0.96	1.00	1.00	0.99	0.98	1.00	1.00	1.00	0.992
International Airlines	1.00	1.00	1.00	0.92	0.96	1.00	1.00	1.00	0.985
Shenzhen Airlines	0.99	0.98	0.90	0.91	1.00	1.00	1.00	0.79	0.947
Changan Airlines	0.64	0.95	0.89	1.00	0.97	1.00	0.96	1.00	0.927
Eastern Airlines	1.00	0.93	1.00	0.80	0.92	0.89	0.88	0.88	0.913
Okay Airways	1.00	0.92	1.00	0.67	0.76	0.71	0.78	0.91	0.843
Sichuan Airlines	1.00	1.00	0.92	0.70	0.75	0.80	0.74	0.69	0.824
Shandong Airlines	1.00	0.86	0.86	1.00	0.71	0.65	0.75	0.72	0.818
Shanghai Airlines	1.00	0.82	1.00	0.79	0.68	0.67	0.68	0.64	0.785
Kunming Airlines	0.60	0.80	0.77	0.51	0.81	0.82	0.89	0.75	0.742
Yunnan Airlines	0.62	0.87	0.84	0.71	0.51	0.76	0.85	0.72	0.736
Capital Airlines	0.62	0.65	0.63	0.57	0.60	0.73	1.00	0.88	0.711
Lucky Air	0.49	0.86	0.81	0.94	0.61	0.65	0.69	0.62	0.707
Chengdu Airlines	0.50	0.76	0.75	0.67	0.69	0.71	0.82	0.52	0.676
Chongqing Airlines	0.40	0.69	0.63	0.46	0.62	0.60	0.61	0.54	0.569
Tianjin Airlines	0.37	0.42	0.48	0.56	0.67	0.62	0.68	0.65	0.558
Hebei Airlines	0.32	0.72	0.72	0.49	0.62	0.58	0.54	0.45	0.555
China Express Airlines	0.21	0.26	0.31	0.21	0.12	0.17	1.00	0.13	0.301

Analysis of regression results

Data were processed using Stata 14.0 to obtain the regression results shown in Table 4. The multicollinearity of the variables was tested before the regression, and no multicollinearity was found between the variables. Thus, each influencing factor could be analysed (Table 4).

Average flight distance is positively correlated with airline environmental efficiency ($p < 0.01$). The longer the average flight distance, the larger the average transportation distance and the higher the transportation efficiency, which can help improve environmental efficiency. In addition, the longer the average flight distance, the longer the cruising distance, which is when the aircraft is in its most fuel-efficient phase. The longer

the average flight distance, the better the airline can save energy and reduce emissions, thus improving environmental efficiency. Therefore, airlines can improve environmental efficiency by optimizing routes to increase average flight distance.

Table 4

Tobit regression results

Independent variable	Correlation coefficient	<i>t</i>	$p > t $
Average flight distance	0.003***	5.04	0.000
Load factor	0.019***	10.67	0.000
Fuel consumption per ton-km	-0.029***	-3.10	0.002
Market share	0.946***	2.49	0.007
Proportion of cargo and mail turnover	1.940***	7.16	0.000
Constant term	-1.127***	-6.96	0.000

*** $p < 0.01$

Load factor is positively correlated with airline environmental efficiency ($p < 0.01$). Load factor can effectively reflect the utilization of the airline's capacity. The higher the load factor, the higher the utilization of the airline's input capacity, which can promote the airline's environmental efficiency. For example, Spring Airlines, which reached the SBM-DEA validity level for environmental efficiency for eight consecutive years, maintained a high load factor. This suggests that airlines can effectively improve environmental efficiency by enhancing their operational capabilities and increasing their load factors.

Fuel consumption per ton-km is negatively correlated with airline environmental efficiency ($p < 0.01$). Fuel consumption per ton-km can effectively reflect an airline's jet fuel utilization. The smaller the fuel consumption per ton-km, the smaller the airline's unit emissions, which is more conducive to improving environmental efficiency. Therefore, airlines can improve environmental efficiency by reducing fuel consumption per ton-km.

Market share and proportion of cargo and mail turnover are positively correlated with airline environmental efficiency ($p < 0.01$). The greater the market share, the better the airline's economic benefits. The airline will therefore invest more in energy conservation and emission reduction, which will improve environmental efficiency. The proportion of cargo and mail turnover can reflect the degree of cargo-space utilization. The higher the cargo and mail turnover, the higher the transportation efficiency, which can improve the airline's environmental efficiency.

Conclusion

Using an SBM-DEA model, this study measured the environmental efficiency of 20 representative airlines in China from 2010 to 2017. A Tobit regression model was used to empirically analyse the factors influencing airline environmental efficiency. The conclusions are as follows:

1. The average environmental efficiency of 20 airlines from 2010 to 2017 was 0.78. The airlines with the highest environmental efficiency were Spring Airlines, China Southern Airlines, and Hainan Airlines, while Chongqing Airlines, Tianjin Airlines, Hebei Airlines, and China Express Airlines had relatively low environmental efficiency.

2. Tobit regression showed that average flight distance, load factor, market share, and proportion of cargo and mail turnover had a positive effect on airline environmental efficiency. Meanwhile, fuel consumption per ton-km had a negative effect on environmental efficiency.

Based on the above conclusions, the following suggestions for improving airline environmental efficiency are proposed:

1. Strengthen airline awareness of carbon emission reduction

Based on the measurement results, most airlines in China have room for carbon emission reduction. Airlines must fully recognize the effect of carbon emissions on environmental efficiency. Although China's airlines are not included in the EU's carbon emission trading system, they should formulate comparable energy conservation and emission reduction guidance manuals based on certain international standards and implement them in all aspects of production and operation to save energy and reduce emissions. China's civil aviation industry currently faces severe energy-saving and emission-reduction tasks. Apart from strengthening management, airlines can also adopt measures such as engine renewal, winglet installation, ground traction to reduce ground taxiing, and auxiliary power unit (APU) replacement to reduce carbon emissions.

2. Optimize route network layout

Airline route network optimization is important for optimizing resource allocation and improving environmental efficiency. With the advent of high-speed rail, airlines need to further segment the market and adjust route network layouts. For short-haul routes overlapping with high-speed rail, airlines have relatively weak competitiveness. By choosing a strategy of joint transport with high-speed rail, airlines can concentrate their advantageous resources to develop domestic long-haul routes and international routes, and thus gradually increase average flight distance and load factors.

3. Increase Research & Development investment and promote operational innovation

The state should increase support for aviation industry Research & Development (R&D), ensure the effectiveness, timeliness, and pertinence of R&D investment, and support the leading role of technological innovation in airline carbon emission reduction. Meanwhile, aviation enterprises must increase their own R&D investment, further orient the whole production process toward energy conservation and emission reduction, improve fuel efficiency, and reduce fuel consumption per ton-km. At the same time, to improve environmental efficiency, airlines should promote operational innovation, maximize the use of existing equipment and technology, introduce advanced technologies, enhance their core competitive competency, and gradually increase their market share.

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