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Growth and Decomposition of Total Factor Productivity in China's Air Transport Industry under Carbon Emission Constraints

Hualei Ju [1], Zihong Chen [2,*]

[1] College of Economics, Northwest University of Political Science and Law , Xi'an 710122, China
[2] Beijing Normal University , Beijing 100875, China
[*]Corresponding author e-mail:chenzihong01@outlook.com

ABSTRACT. *The total factor productivity of the air transport industry under carbon emission constraints has attracted much attention. Based on the data of Chinese air transport listed companies from 2012 to 2018, the super-efficiency DEA and Malmquist-luenberger index were used to measure its total factor productivity and after further decomposition, it is found that: ①both the low-carbon total factor productivity and the traditional factor productivity of aviation transport enterprises showed a changing trend of rising at first and then decreasing. However, the low-carbon total factor productivity was generally higher than the traditional total factor productivity; ②after further decomposition of the low-carbon total factor productivity, it is found that technological advance is the main driving force behind the low-carbon total factor growth rate, and scale efficiency limits the improvement of technical efficiency.*

KEYWORDS: *air transport industry, low-carbon total factor productivity, the super-efficiency DEA and Malmquist-luenberger index*

1 Introduction

With the rapid development of the global economy and the sustained growth of transportation, the air transport industry has become an important part of the world economy and transportation facilities, supporting the steady economic development of countries in the world. However, the energy-intensive air transport industry, whose carbon emissions worsening the air quality stay in the atmosphere for a long time, especially at high altitude, is both a major user of carbon-based fuels and a chief culprit of the greenhouse effect. According to the fifth assessment report of the Intergovernmental Panel on Climate Change (IPCC), 11% of man-made greenhouse gas emissions from 2000 to 2010 came from the transportation industry, of which the carbon dioxide emissions from air transport accounted for 2% of the

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total global man-made carbon dioxide emissions. Therefore, as the world's second largest air transport system, China's aviation carbon emissions have received significant attention in order to achieve the temperature control goal of "1.5 degrees Celsius" set by the Paris Agreement in 2015. Then, under the premise of coordinated development with the environment, how will the efficiency and productivity of China's air transport industry change? Correctly answering the above question is of great importance to the effective response to the carbon emissions trading system and to the sustainable development of China's air transport industry under the constraints of carbon emissions.

The existing research on the total factor productivity(TFP) of the air transport industry is mainly conducted from the following aspects. Most scholars conduct research on TFP under environmental constraints from the perspective of the entire logistics industry. Tang Jianrong et al. (2018) based on provincial panel data, using DEA-BCC method and threshold regression model to measure logistics efficiency, concluded that the logistics efficiency of only a few provinces is shown as effective [1]; also, there are other scholars take airlines as the research object, such as YANG (2016) and Yu Jian (2007) who use the Malmquist index to measure and analyze the TFP of major airlines in different regions, but the environmental factors were not taken into the research framework[2-3]; besides, only a few studies have focused on the TFP of airlines that under the constraint of carbon emission, such as Scotti (2015) and Lee (2015) who take environmental factors into the research, using the ML index to measure the TFP of airlines, pointed out that the TFP which under environmental constraints is lower than the traditional TFP[4-5], and the performance measurement with environmental constraints is more in line with the reality of emission reduction and climate change; Huang Ganyan (2018) used GML index to analyze the changes of the TFP of Chinese airlines in 2009-2013, and concluded that neglecting carbon dioxide emissions would exaggerate the performance of Total Factor Productivity Growth. As can be seen from the above studies, the existing research results may have the following deficiencies: (1) Although the issue of carbon emissions in the air transport industry is increasingly valued, relevant research results are still insufficient; (2) There is heterogeneity among different departments of the logistics industry[7], so describing the changes in the TFP of the air transport industry with total or approximate industry data may distort the facts. Therefore, this paper attempts to measure the TFP of the air transport industry by using the super-efficiency DEA-Malmquist-luenberger model with introducing carbon emissions as undesirable output, and then evaluate its development, and make further comparison to analyze the difference between this TFP and the traditional TFP.

2 Methodology

In this paper, the Malmquist-Luenberger productivity index approach based on super-efficiency DEA-DDF is adopted and the calculation ideas are as follows:

First, construct an effective frontier of the economy through the Super-efficiency DEA Model and environmental technology. In order to bring the undesirable output

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into the analytical framework, it is necessary to construct the production frontiers under the simulation of environmental technologies, and to adopt the Directional Distance Function that can consider both the increase of expected output and the decrease of undesirable output to evaluate the distance between the decision making units and the production frontiers.

Suppose the decision making units are $k = 1 \cdots K$ and the period are $t = 1 \cdots T$, and based on DEA technology, the environmental technology set $P(x)$ can be expressed as follows, where z_k^t is the weight vector, which represents the weight of decision making units in each period when the production frontier is constructed.

$$P(x) = \{(x^t, y^t, b^t):$$

$$\sum_{k=1}^{K} z_k^t x_{kn}^t \ll x_n^t \ \ n = 1 \cdots N;$$

$$\sum_{k=1}^{K} z_k^t y_{km}^t \gg y_m^t \ \ m = 1 \cdots M;$$

$$\sum_{k=1}^{K} z_k^t b_{ki}^t = b_i^t \ \ i = 1 \cdots I;$$

$$\sum_{k=1}^{K} z_k^t = 1 \ ; \ z_k^t \gg 0 \ \ k = 1 \cdots K\}.$$

Second, the Directional Distance Function (DDF) is used to calculate the distance between each production decision unit and the effective frontier. The DDF can be defined as:

$$\overrightarrow{D_0}(x, y, b; g) = \sup\left\{\beta: \left(y + \beta_{g_{y'}}, b - \beta_{g_b}\right) \in p(x)\right\}$$

Here, g is the total direction vector, and $g = (g_{y'} - g_b)$ represents the direction of the increase of expected output and the decrease of undesirable output. The linear programming formula of the DDF super-efficiency model is expressed as:

$$\overrightarrow{D_0}(x^t, y^t, b^t; g^t) = max\beta$$

$$s.t. \ \sum_{\substack{k=1 \\ k \neq j}}^{K} z_k^t x_{kn}^t \ll (1-\beta) x_n^t \ \ n = 1 \cdots N$$

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$$\sum_{\substack{k=1\\k\neq j}}^{K} z_k^t y_{km}^t \gg (1+\beta) y_m^t \;\; m = 1 \cdots M;$$
$$\sum_{\substack{k=1\\k\neq j}}^{K} z_k^t b_{ki}^t = (1-\beta)\, b_i^t \;\; i = 1 \cdots I;$$
$$\sum_{\substack{k=1\\k\neq j}}^{K} z_k^t = 1 \; ; \; z_k^t \gg 0 \;\; k = 1 \cdots j-1, j, j+1 \cdots K.$$

Further, the value of Malmquist-Luenberger index (ML index) is calculated based on the two-period DDF, and according to chung et al. (1997), the ML index from *t* to *t + 1* is defined as:

$$ML_t^{t+1} = \left\{ \frac{[1+\overrightarrow{D_0^t}(x^t, y^t, b^t; g^t)]}{[1+\overrightarrow{D_0^t}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})]} \times \frac{[1+\overrightarrow{D_0^{t+1}}(x^t, y^t, b^t; g^t)]}{[1+\overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})]} \right\}^{\frac{1}{2}}$$

Meanwhile, in order to decompose the ML index and explore its driving factors, ML is decomposed into technological progress (TC) and technical efficiency (EC), and EC can be further decomposed into pure technical efficiency (PEC) and scale efficiency (SEC).

$$ML_t^{t+1} = TC_t^{t+1} \times EC_t^{t+1}$$
$$ML_t^{t+1} = TC_t^{t+1} \times PEC_t^{t+1} \times SEC_t^{t+1}$$

$$TC_t^{t+1} = \left\{ \frac{\left[1+\overrightarrow{D_c^{t+1}}(x^t, y^t, b^t; g^t)\right]}{\left[1+\overrightarrow{D_c^t}(x^t, y^t, b^t; g^t)\right]} \times \frac{\left[1+\overrightarrow{D_c^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]}{\left[1+\overrightarrow{D_c^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]} \right\}^{\frac{1}{2}}$$

$$EC_t^{t+1} = \frac{1+\overrightarrow{D_c^t}(x^t, y^t, b^t; g^t)}{1+\overrightarrow{D_c^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$

$$PEC_t^{t+1} = \frac{1+\overrightarrow{D_v^t}(x^t, y^t, b^t; g^t)}{1+\overrightarrow{D_v^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})}$$

$$SEC_t^{t+1} = \frac{\left[1+\overrightarrow{D_c^t}(x^t, y^t, b^t; g^t)\right]}{\left[1+\overrightarrow{D_v^t}(x^t, y^t, b^t; g^t)\right]} \Big/ \frac{\left[1+\overrightarrow{D_c^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]}{\left[1+\overrightarrow{D_v^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})\right]}$$

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In the above formulas, where $\overrightarrow{D_0^t}(x^t, y^t, b^t; g^t)$ and $\overrightarrow{D_0^{t+1}}(x^{t+1}, y^{t+1}, b^{t+1}; g^{t+1})$ represent the distance function based on the technology of t period and t + 1 period, and $\overrightarrow{D_c^t}$ and $\overrightarrow{D_v^t}$ represent the directional distance functions based on the conditions of constant returns to scale and variable returns to scale, respectively. Therefore, when ML, TC, PEC, and SEC are greater than 1, they respectively represent the improvement of TFP, technological progress, pure technological efficiency and scale efficiency from a low-carbon perspective. Conversely, when ML, TC, PEC, and SEC are less than 1, it means the decline of TFP, pure technical efficiency, and scale efficiency while the improvement of technology from a low-carbon perspective.

3 Research Design

3.1 Sample Selection and Data Sources

According to the sector classification of the China Securities Regulatory Commission in 2012, the A-share listed companies in the air transport industry are selected as the research object. After excluding ST, * ST and the listed companies with incomplete financial data, the remaining seven listed companies are Shenzhen Airport, CITIC Amanoatae, Shanghai Airport, China Southern Airlines, China Eastern Airlines, HNA Holdings and Air China. And the data sources include CSMAR database, public disclosure of the annual reports of listed companies, and “Annual Data of Major Cities” of China’s National Bureau of Statistics.

3.2 Indicator Selection

To objectively evaluate the TFP level of the research objects in a low-carbon perspective, in terms of input indicators, the average number of employees, operating costs and total assets are selected[8]-[9]; in terms of desirable output indicators, operating income and net profit are selected. As for the undesirable output indicators, it is confined to the micro-enterprises. Since the lack of relevant corporate social responsibility reports is more serious and it is difficult to obtain the emission data of environmental pollution, the aviation oil cost (vehicles maintenance) for each year is selected as the undesirable output indicator. However, due to the negative value of the net profit in the output variable, it is necessary to standardize the dispersion of the data. And after processing, the value range of this indicator data is [0.1, 1], which meets the requirements of the model.

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4. Empirical Study

4.1 Traditional Total Factor Productivity and Low-carbon Total Factor Productivity

Using the above-mentioned intertemporal panel data, based on the super-efficiency DEA model and the Malmquist-lunberger model, the low-carbon total factor productivity index GMI of seven listed air transport companies in China from 2013 to 2018 was calculated. In addition, using the traditional super-efficiency and malmquist model, this paper also estimates the TFP value MI under the condition of neglecting the undesirable output. At the same time, the two indexes are decomposed into GEC, GTC and EC, TC, and GEC and EC are further decomposed into GSEC, GPEC and SEC and PEC. The results are presented in Table 1.

Table1 2013-2018 Traditional and Low Carbon Total Factor Productivity and Its Decomposition

Year	Traditional TFP					Low Carbon TFP				
	MI	EC	TC	SEC	PEC	GMI	GEC	GTC	GSEC	GPEC
2013	0.946	1.012	0.940	0.972	1.041	0.955	1.010	0.947	0.967	1.050
2014	0.981	0.992	0.988	1.003	0.990	1.014	1.005	1.010	1.013	0.993
2015	1.017	1.015	1.004	1.049	0.972	1.090	1.005	1.084	1.017	0.988
2016	1.010	1.041	0.970	0.994	1.047	1.039	1.033	1.006	1.017	1.017
2017	0.963	0.945	1.022	0.944	1.017	0.957	0.955	1.004	1.003	0.953
2018	1.033	1.004	1.031	0.966	1.046	1.022	0.999	1.024	0.988	1.011
Average	0.992	1.001	0.993	0.988	1.019	1.013	1.001	1.012	1.001	1.002

From Table 1, it can be seen that there is a certain gap between the low-carbon TFP and the traditional TFP of the 7 air transport companies in 2013-2018. From the perspective of low carbon, the TFP value is 1.013, showing an average annual growth rate of 1.3%. By contrast, the traditional TFP value is 0.992, which shows an average annual decline of 0.8%. Obviously, GMI is greater than MI, which means that ignoring environmental factors underestimates the growth of TFP in the air transport industry. This fact reveals that China's "Twelfth Five-Year Plan" and "Thirteenth Five-Year Plan", which promote energy conservation and emission reduction, speed up the construction of ecological civilization, and strengthen environmental supervision, have played an important role.

After further decomposition and analysis of TFP, it can be found that from the perspective of low carbon, the average annual growth rate of technological progress is 1.2% and that of technological efficiency is 0.1% in 2013-2018, which proves that the growth of TFP in the perspective of low carbon is mainly driven by technological progress. In the traditional perspective, the average annual growth rate of EC is 0.1%, the same as that of GEC. Compared with GTC, the average decline

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of TC is 0.7%. Thus, the decline in traditional TFP is mainly caused by the decline in technological progress, and the promotion in technical efficiency cannot offset the decline in technological progress.

4.2 Temporal Evolution Analysis on Total Factor Productivity and Decomposition in the Air Transport Industry

In order to analyze and compare the dynamic change trends of TFP under environmental constraints and non-environmental constraints, Figure 1 shows the time-series chart of GMI and MI and their decomposition variables from 2013 to 2018.

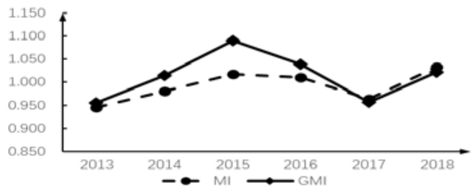

FIG. 1 Time-series Chart of MI and GMI

As shown in Figure 1, MI and GMI experienced a process of increasing first and then decreasing during 2013-2016, and both reached their peak in 2015. From 2013 to 2016, the low-carbon TFP is higher than the traditional TFP, which shows that the energy saving and emission reduction policies in the mid to late stages of the "Twelfth Five-Year Plan" have a significant effect on the promotion of TFP.

Moreover, at the end of the "Twelfth Five-Year Plan" in 2015, in order to achieve an emissions target of 16% reduction in energy consumption per unit of GDP and 17% reduction in CO2 emissions per unit of GDP, the difference between low-carbon TFP and traditional TFP reached the maximum. After 2015-2017, traditional TFP and low-carbon TFP began to converge and gradually coincided. And in 2017 and 2018, traditional TFP was slightly higher than low-carbon TFP by 0.6% and 1.1% respectively.

Technological progress (TC) effect refers to the reduction of pollution emissions and ecological damage through the progress of pollution treatment technology or production technology, so as to establish a compensation mechanism of non-renewable resource constraint, and then promote the efficiency of production. The efficiency change (EC) effect is also known as the "catch-up" effect, which characterizes the speed of a DMU moving to the production frontier, that is, the latter can achieve the goal of "catch-up" by imitating the first mover. And there will be catch-up effects when resource allocation is optimized, economies of scale are improved, and environmental constraints are alleviated. From the analysis of Figure 2, it can be observed that the technical efficiency that represents the catch-up effect, regardless of whether carbon emissions are considered, showed a steady uptrend in

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2013-2016, with only 0.992 of the traditional technical efficiency in 2014 being slightly less than 1, and the rest being greater than 1. This explains that during this period, both MI and GMI are driven by technical efficiency. However, in 2017, both indexes fell to their lowest point, with EC at 0.945 and GEC at 0.955. By comparing the efficiency of traditional and low-carbon technologies, it can be found that the change tendency of the two are synergistic and relatively mild. And in 2014, though the difference between the two was the largest, it was only 0.013, which illustrates that whether environmental factors are taken into account has little effect on technical efficiency. The reason may be that although China has established relevant emission reduction systems and taken management measures, due to the short implementation time, and the system needs a certain amount of time to adapt and to be adjusted, so the efficiency of low-carbon technology is not significantly different from that of traditional technology.

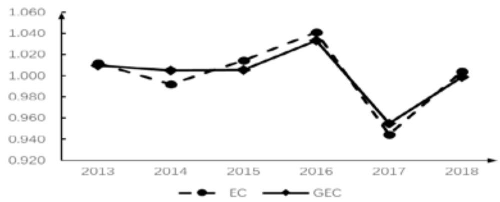

FIG. 2 Time-series Chart of EC and GEC

According to Figure 3, the index of progress in traditional technology gradually increased from 0.94 in 2013 to 1.03 in 2018, but none of them significantly exceeded 1 in 2013-2016, which elucidates that technological progress is the main factor dragging down the growth of traditional TFP, and there is a phenomenon of technological degradation. However, technological degradation does not conform to objective reality. In contrast, the index of progress in low-carbon technology is greater than 1 except for 2013, demonstrating that the low-carbon TFP is more realistic and has a better referential value on the establishment of policy. Furthermore, by comparing the index of progress in traditional and in low-carbon technology, we can conclude that the difference between the two is obvious, that is, GTC is much higher than TC. And in 2015, the index of low-carbon technological progress reached 1.084, where the difference between the two reached the greatest 0.08. This illustrates that technical progress plays a crucial role in promoting low-carbon TFP.

Since 2013, air transport companies have taken a series of steps, such as flight paths optimization, winglets installation, introduction of new aircraft of B787, A350 and etc., elimination of gas-guzzling aircraft, engine modification, implementation of single engine taxiing and other technologies, to lower fuel consumption and achieve the goal of energy-saving and emission reduction quickly. Therefore, the calculated index is in accord with the objective facts.

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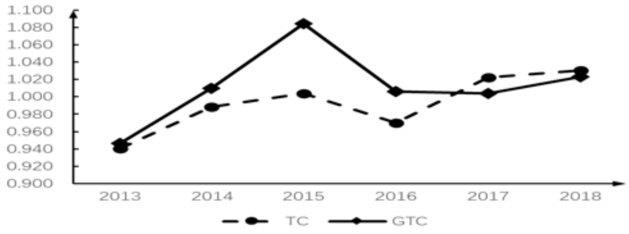

FIG. 3 Time-series Chart of TC and GTC

5. Conclusion

In this paper, carbon emission is regarded as undesirable output, and the temporal variation and individual differences of low-carbon TFP and its decomposition of listed airlines in China are evaluated by adopting super-efficiency DEA-Malmquist Luenberger model, and the main conclusions reached are as follow:

Firstly, low carbon TFP is generally higher than traditional TFP, and the growth of low carbon TFP is mainly driven by technological progress. From 2012 to 2018, the average annual growth rate of low-carbon TFP of the air transport industry was 1.3%, while the average yearly decline of traditional TFP was 0.8%, which proves that neglecting environmental factors underestimates the growth of TFP in China, moreover, China's policies oriented by economic growth and energy-saving and emission reduction have made some achievements in the air transport industry. Secondly, for the factors of decomposition of TFP, the efficiency changes of the traditional technology is basic anastomotic with that of low-carbon technology from 2013 to 2018, whereas the progress of low-carbon technology is generally higher than that of traditional technology, with an annual growth difference of 1.9%. This confirms that the advanced emission reduction technologies are the key factors for the growth of low-carbon TFP in the air transport industry. Thirdly, from the perspective of temporal variation, the progress index of low-carbon and traditional technology changes from deviation to convergence, and finally changes synergistically. This demonstrates that the situation of emission reduction in air transport industry is still grim, and the effectiveness of emission reduction has gradually weakened. As a result, the air transport industry should pay more attention to optimization of resource allocation and the technical efficiency promotion of economies of scale.

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