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INTEGRATED AIRLINE PRODUCTIVITY PERFORMANCE EVALUATION WITH CO_2 EMISSIONS AND FLIGHT DELAYS

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ABSTRACT

This paper evaluates the airline productivity change by applying a modified global Malmquist productivity index (GMPI) model that incorporates both CO_2 emissions and flight delays into the estimation model. Statistical inference is also performed on GMPI results using the bootstrapping method. Empirical research was conducted on 15 international airlines during 2011-2017. The empirical results showed the productivity of all airlines experienced a slight increase over 2011-2017. The results of GMPI and five driving factors of the 15 airlines were test to be reliable in most cases. Although efforts were made to restrain both CO_2 emissions and flight delays, airline CO_2 emission reduction was still inadequate to influence the productivity of airlines. Punctuality improvement did not facilitate overall productivity growth as expected. The additional cost paid by airlines to optimize their punctuality performance may not always lead to actual gains in productivity in the short term. Efficiency change and technological change were the major driving factors for the growth of airline productivity. Fifteen airlines had differed efficiency and technology features when considering the scale efficiency. Airlines need to choose targeted operational approaches to improve their productivity.

Keywords: airline performance, global Malmquist productivity index, airline CO2 emissions, flight delays.

1. INTRODUCTION

The international civil aviation industry has experienced rapid growth over the past few decades, boosted by a population boom and economic prosperity [1]. Inevitably, airline companies are faced with more and more fierce competition [2], and they have devoted to improving operational performance and pursuing greater competitiveness [3-7].

With the increasing environment and service quality awareness of consumers, new challenges emerged for airlines. One of these is that the environmental issue with the highest profile is the CO_2 emissions of the airline [8]. Some scholars have focused on measuring the airline performance with airline CO2 emissions as the undesirable output in recent years [9-12].

Service quality is a further important issue for airlines. Improving service quality helps the airline retain customers and maintain its market position. Whether a flight can arrive at the destination on time is always of great concern to consumers in airline quality rating [13]. In fact, flight delay has become a severe problem to airlines as it may lead to financial and technical inefficiency [14]. Flight delay has been the subject of several existing literatures for its potential effect on the airline performance [15-17][3].

Based on the existing literature, this paper provides an evaluation of airline productivity by constructing a global Malmquist productivity model with undesirable output and attributes. The main contributions of this study are that: This paper proposes an integrated airline performance evaluation method that considers the effects of CO_2 emissions and flight delays on airline productivity. This integrated airline performance evaluation approach on airline productivity, which incorporates statistical inference by performing a bootstrapping procedure, provides a reliable framework for the assessment of the underlying sources of airline productivity change. An empirical study was conducted to analyze efficiency, technology and punctuality changes' influence on airline productivity, which helps to monitor changes in airline productivity and provide management advice.

2. METHODOLOGY

To incorporate both CO2 emission and flight delays in airline productive performance evaluation, we use a modified Malmquist productivity index model of Färe et al.[18] . Given that airline operators tend to optimize their input to achieve equivalent output value, we used input-oriented Malmquist productivity index in this paper. Also, a global Malmquist index (GMPI)is used to overcome the weakness of geometric mean Malmquist index (i.e. non-circularity and infeasibility) [19].

We construct the technology set, in which each company uses labor (L) and fixed asset investment (K) as inputs to revenue passenger kilometers (Y) as desirable output, CO_2 emissions (C) as undesirable outputs. Besides, we take the input attribute, the flight delay rates (D), as a proxy for punctuality on the input side; the passenger load factor (LF) is regarded as a proxy for market performance on the output side. As the passenger load factor is a typical market performance index in the airlines, we incorporate it into the model to testify whether punctuality reduction has influence on airlines' operations.

The production technology set can be described as:

$$S = \{(\mathrm{L}, \mathrm{K}, FD, \mathrm{Y}, \mathrm{C}, LF): (\mathrm{L}, \mathrm{K}, FD) \text{can produce } (\mathrm{Y}, \mathrm{C}, LF)\} \quad (1)$$

The input-oriented Shephard distance function, which yields the maximum possible reduction of inputs when keeping the other factors fixed, is defined in Eq (2). θ is the reciprocal of the distance function and represents the airline's technical efficiency.

$$D_I(\mathrm{L}, \mathrm{K}, D, \mathrm{Y}, \mathrm{C}, LF) = sup\left\{\theta \middle| \left(\frac{L}{\theta}, \frac{K}{\theta}, \frac{D}{\theta}, Y, C, LF\right) \in S\right\} \quad (2)$$

The distance function can be calculated by estimating certain DEA Models.

Further, input-oriented GMPI is defined as Eq (3). The index could be further decomposed into factors related to attribute changes ($ACH_i^{s,t}$) and physical variable changes ($PCH_i^{s,t}$). The subscript c in the distance function represents a constant return to scale, while v represents a variable return to scale; i represents the i-th decision making unit (DMU). Superscripts s and t represent the base period and the study period, respectively.

$$GMPI_i^{s,t} = \frac{D_c^G(L_i^s, K_i^s, Y_i^s, C_i^s, FD_i^s, LF_i^s)}{D_c^G(L_i^t, K_i^t, Y_i^t, C_i^t, FD_i^t, LF_i^t)} = ACH_i^{s,t} \times PCH_i^{s,t} \quad (3)$$

Following Färe, Grosskopf, & Roos (1995), we assume that the distance function is multiplicatively separable in attributes and input/outputs, as $D_c^G(L_i^t, K_i^t, Y_i^t, C_i^t, FD_i^s, LF_i^s) = \widehat{D}_c^t(L_i^t, K_i^t, Y_i^t, C_i^t) A_c^G(FD_i^s, LF_i^s)$. As such, the global Malmquist productivity can be decomposed into 5 factors.

$$\begin{aligned} GMPI_i^{s,t} &= \frac{A_c^G(FD_i^s, LF_i^s)}{A_c^G(FD_i^t, LF_i^t)} \times \frac{\widehat{D}_c^G(L_i^s, K_i^s, Y_i^s, C_i^s)}{\widehat{D}_c^G(L_i^t, K_i^t, Y_i^t, C_i^t)} \quad (4) \\ &= \frac{A_c^G(FD_i^s, LF_i^s)}{A_c^G(FD_i^t, LF_i^t)} \times \frac{\widehat{D}_v^s(L_i^s, K_i^s, Y_i^s, C_i^s)}{\widehat{D}_v^t(L_i^t, K_i^t, Y_i^t, C_i^t)} \times \frac{\widehat{D}_c^s(L_i^s, K_i^s, Y_i^s, C_i^s)/\widehat{D}_v^s(L_i^s, K_i^s, Y_i^s, C_i^s)}{\widehat{D}_c^t(L_i^t, K_i^t, Y_i^t, C_i^t)/\widehat{D}_v^t(L_i^t, K_i^t, Y_i^t, C_i^t)} \\ &\times \frac{\widehat{D}_v^G(L_i^s, K_i^s, Y_i^s, C_i^s)/\widehat{D}_v^s(L_i^s, K_i^s, Y_i^s, C_i^s)}{\widehat{D}_v^G(L_i^t, K_i^t, Y_i^t, C_i^t)/\widehat{D}_v^t(L_i^t, K_i^t, Y_i^t, C_i^t)} \\ &\times \left[\frac{\widehat{D}_c^G(L_i^s, K_i^s, Y_i^s, C_i^s)/\widehat{D}_v^G(L_i^s, K_i^s, Y_i^s, C_i^s)}{\widehat{D}_c^s(L_i^s, K_i^s, Y_i^s, C_i^s)/\widehat{D}_v^s(L_i^s, K_i^s, Y_i^s, C_i^s)} \times \frac{\widehat{D}_c^t(L_i^t, K_i^t, Y_i^t, C_i^t)/\widehat{D}_v^t(L_i^t, K_i^t, Y_i^t, C_i^t)}{\widehat{D}_c^G(L_i^t, K_i^t, Y_i^t, C_i^t)/\widehat{D}_v^G(L_i^t, K_i^t, Y_i^t, C_i^t)}\right] \\ &= ACH_i^{s,t} \times PECH_i^{s,t} \times SECH_i^{s,t} \times PTCH_i^{s,t} \times STCH_i^{s,t} \end{aligned}$$

They are the factors of punctuality change (ACH), pure efficiency change (PECH), scale efficiency change (SECH), pure technological change (PTCH) and technological scale change (STCH). For these factors, Values greater than 1 indicate an improvement in productivity performance, while values less than one imply deterioration. The bootstrap is also applied here to perform statistical inference on GMPI results [20].

3. DATA

15 representative international airlines are selected as samples in the empirical research. They are Delta (DAL), Southwest(SWA), Alaska(ASA), Air France-KLM(AFR-KLM), Lufthansa(CLH), Emirates(UAE), China Southern(CSN), Air China(CCA), China Eastern(CES), Hainan Airline(CHH), Cathay Pacific Airways(CPA), Singapore(SIA), All Nippon Airlines(ANA), Korean Air(KAL), Qantas Airways(QFA). Time period ranges from 2011 to 2017. These airlines come from Asia, America, Europe and Oceania and are all representative airlines in each country. All the data are self-collected from open reports of these airlines.

4. RESULTS AND DISCUSSION

Empirical research was conducted on the 15 selected airlines from 2011 to 2017. First, the global technical efficiencies of 15 airlines were calculated with DEA techniques, as shown in Fig 1.

According to Fig. 1, the incorporation of CO_2 emissions made little difference for the efficiency estimation of these airlines. It indicates that though airlines focus on CO_2 emission reduction, their efforts were still inadequate to influence productivity during 2011-2017. In comparison, the inclusion of punctuality attributes imposed a greater influence on the estimation results. The efficiency scores obtained when considering the punctuality attributes were higher than those obtained with a purely technical frontier for all airlines. It is common case for DEA to get higher scores when incorporating more variables, as the production frontier would shrink with more constraints imposed in the linear programming. Still, airlines with better punctuality performance, such as ANA, CLH, ASA, and AFR-KLM (around 15%), tend to take relatively greater advantage of this modification in productivity performance evaluation. The results imply that the technical efficiency of airlines with poor punctuality performance was overestimated in a model without punctuality attributes. Punctuality improvement enables airlines to increase customer satisfaction, rationalize their utilization of resources, and attract more passengers.

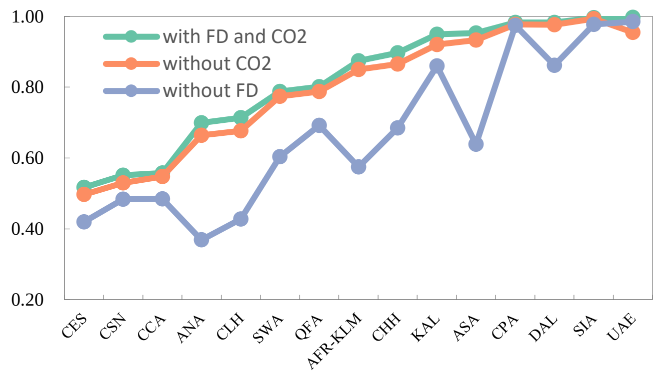

Fig 1. Average global technical efficiency of 15 airlines

In general, airlines in North America stayed at high efficiency level among the 15 airlines. North American airlines took the lead in aviation industry, and they can easily approach the cutting-edge technology and management experience. European airlines were less efficient than American airlines. Although Europe was also the most important aviation market besides North America, the development of European airlines was slower than North America. What's more, efficiency scores ranged a lot among Asian airlines, airlines with smaller scales tend to have better technical efficiencies. As most of the Asian airlines had been in the process of technological catching up, it would be easier for airlines with smaller scales to modify their operations and achieve more gains in efficiency. The "Big Three airlines" of China (CES, CSN and CCA), which was large in scale, would take more time in technical efficiency improvement.

The calculation of GMPI and its driving factors can be got using Eq (3) and (4). Results are shown in Fig 2. In general, there was a slight increase in productivity for the 15 airlines. When not considering punctuality change in the model, airlines' productivity had been increasing during all years. Contrary to general belief, punctuality change did not facilitate airline productivity growth during the sample period.

Airline productivity with punctuality change factor experienced a slight drop (around 3%) during 2012-2016, which was mainly a side effect of punctuality change. The airlines' punctuality was improved at a certain degree during 2014-2016, but there was no apparent increase in airlines' passenger load factor during these years. The results indicate that market performance of these airlines did not greatly improve with flight delay reduction. Airlines paid an additional cost to optimize their punctuality performance; however, the on-time performance improvement apperceived by customers may not always convert into actual gains in productivity of airlines in the short term.

Physical variable changes, including efficiency change and technological change factors, were the major driving factors for airline productivity growth. The airlines' efficiency had been increasing during the past years, mainly coming from scale efficiency change. Pure efficiency scores of these airlines experienced a slight drop during these years. It shows that the airlines were at the stage of increasing returns to scale (IRS), and they had been expanding their operations to meet the increasing market demand. Most of the airlines benefitted from the expansion of aviation market and had their operational efficiency improved.

Also, the airlines' technology had experienced certain improvement during the study period. With the international aviation turnover increasing rapidly with an annual rate of around 4% (ICAO), airlines have put more efforts into innovating technology during the past few decades. However, there was no progress but a slight drop in technology during 2012-2015. Global economy remained sluggish after recovering from the financial crisis. Particularly, there was a considerable drop in the growth rate of emerging economies in 2012. Stagnate passenger growth, together with the high fuel prices, put burden on airlines' operations and slowed their technology investment. For example, most of the airlines put off updating their fleet in 2012.

PTCH had positive effect on airline productivity. As for technological scale change, airlines were in the stage of decreasing returns to scale during 2012-2015. The airlines' existing technology progress mainly came from the technology import rather than self-dependent innovation, which is unsustainable. After 2015, the situation was improved and airlines' PTCH and TSCH both turned to be positive factors to productivity change.

Based on the GMPI results for 15 airlines from 2011 to 2017, bootstrapping procedure was also applied to perform statistical inference on the GMPI. Table 1 reports the estimates of GMPI, together with its statistical testing results. Also, Table 2 reports the average annual results of GMPI and five driving factors of the 15 investigated airlines. Most of the airlines shared similar trends on GMPI and five driving factors, as mentioned above. The bootstrapping results also show the reliability of the original GMPI results in most cases.

Overall, except for the stagnant development of the aviation industry in certain years, airline productivity had been increasing with the rapid expansion of the industry during 2011-2017.

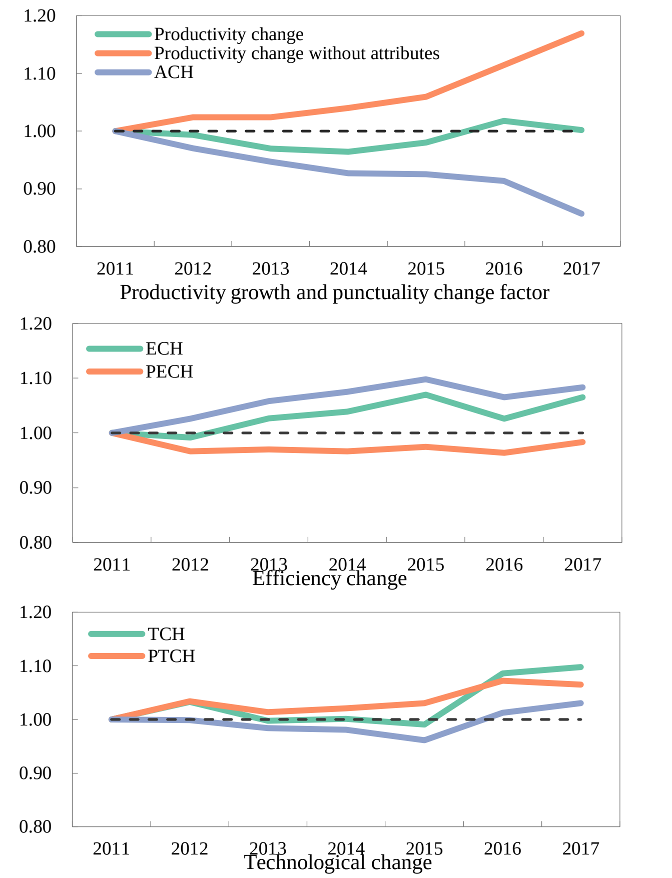

Fig 2. Cumulative productivity growth and its driving factors, 2011-2017

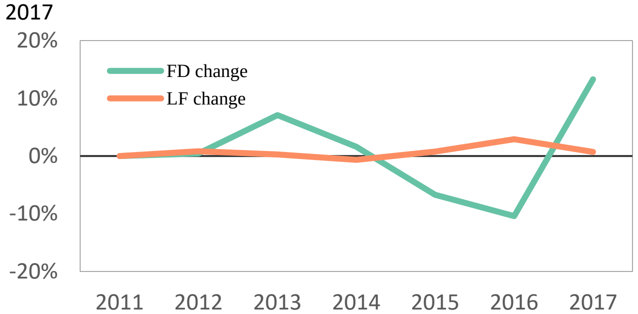

Fig 3. Average flight delay and passenger load factor change during 2011-2017.

The productivity growth was mainly owing to the efficiency improvement and technology progress. A catching-up existed among several less developed airlines. These airlines tend to experience a stronger increase in productivity than the most efficient airlines. Scale efficiency played an important role in both efficiency and technology change. IRS of efficiency mainly occurred in European airlines and in most of the Asian airlines. These airlines benefitted from the expansion of the aviation market and improved their operational efficiencies. Although the aviation industry is still under the progress of expansion in the emerging economies, airlines should also pay more attention to optimizing their management strategies. For airlines of North America, efficiency growth mainly originates from pure efficiency improvement, not scale efficiency. They have advantages in management experience; therefore, they should emphasize structural adjustment of the company. IRS of technology only occurred in North American airlines and in part of Asian airlines. These airlines took the lead in technology innovation and should maintain their technology level and import advanced technology if necessary. However, the technology progress of airlines in Europe and most of Asia originated from pure technology efficiency improvement. These airlines' existing technology progress mainly originates from technology import rather than from self-dependent innovation. They should emphasize the improvement of their own technology innovation ability.

Punctuality change did not facilitate productivity growth as expected, although there were flight delay reductions in half of the airlines. Market performance of the airlines did not greatly improve with flight delay reduction. Thus, the additional cost paid by airlines to optimize their punctuality performance may not always yield actual gains in productivity in the short term.

Table 1. Changes in GMPI during 2011-2017

GMPI	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017
CES	0.9902**	0.9459**	0.9503*	1.1415**	1.0562**	1.0338**
CSN	0.9167**	0.9257**	1.0343**	1.0078**	1.0724**	1.0705**
CCA	0.9929	1.0167**	1.0061*	0.9914**	1.0848**	1.0116**
CHH	0.9396**	0.9867*	0.8331**	0.8964**	1.4442	1.0000**
CPA	0.9732	0.9959**	1.0015	1.0003**	1.0234	1.0063
DAL	1.0548**	0.9658**	1.0104	1.0154**	1.0093**	1.0000**
ASA	0.9950	0.9811**	0.9424**	1.0041**	1.0825**	0.8634**
SWA	1.0739**	0.9742**	0.9637**	1.0824**	1.0042	0.9755*
KAL	1.0000	0.9169**	0.9634**	1.0376**	1.0910	0.9338
QFA	1.0099	0.9840**	1.0749**	1.1234**	1.0073**	1.0179**
AFR-KLM	1.0817**	1.0583**	1.1373**	0.9416**	0.9695*	0.9297**
CLH	0.9704**	1.0056**	1.0888**	0.9261**	0.9208**	0.9808
SIA	1.0000**	1.0000**	0.9981	1.0019	1.0000*	0.9755**
ANA	0.9218**	0.8914**	0.9530	1.1374**	0.8796**	0.9865**
UAE	1.0000**	1.0000**	0.9985	0.9829**	1.0189	1.0000*
Gmean	0.9936	0.9757	0.9946	1.0168	1.0381	0.9845

*the index is significantly different from unity at the 0.1 level

**the index is significantly different from unity at the 0.05 level

Table 2. Annual average change on GMPI and its driving factors

Airline	GMPI	Rank	ACH	PECH	SECH	PTCH	STCH
CES	1.017	2	0.967	1.027	1.005	1.026	0.994
CSN	1.003	7	0.986	0.996	1.005	1.033	0.982
CCA	1.017	4	1.007	0.998	0.992	1.034	0.987
CHH	1.000	9	0.911	1.000	1.088	1.000	1.009
CPA	1.000	8	1.000	1.000	1.000	1.000	1.000
DAL	1.009	6	1.008	1.000	0.988	1.007	1.007
ASA	0.976	14	0.940	1.000	0.974	0.961	1.110
SWA	1.011	5	0.979	0.975	0.992	1.052	1.015
KAL	0.989	12	1.018	1.000	0.994	0.972	1.005
QFA	1.035	1	1.003	1.004	1.012	1.031	0.986
AFR-KLM	1.017	3	0.957	0.964	1.082	1.057	0.964
CLH	0.981	13	0.932	0.929	1.111	1.081	0.942
SIA	0.996	11	1.002	1.000	1.000	0.994	1.000
ANA	0.958	15	0.932	1.072	0.971	0.922	1.071
UAE	1.000	10	0.986	1.000	1.000	1.000	1.014

5. CONCLUSION

This paper evaluates airline productivity and its driving factors by applying a modified global Malmquist index model. Both CO2 emissions and flight delays have been incorporated into the distance function estimation model to identify the effects of efficiency, technology, and punctuality change on airline productivity. The bootstrapping procedure is also applied to perform statistical inference on the GMPI results. Using the integrated airline performance evaluation approach proposed in this paper, an empirical study was conducted on 15 international airlines for the time between 2011 and 2017. The following results can be summarized:

In general, the results of GMPI and five driving factors of the 15 airlines passed the statistical test in most cases, implying the reliability of GMPI results based on DEA calculations. Except for the stagnant development of the aviation industry in certain years, the productivity of most airlines increased with the rapid expansion of the industry during 2011-2017. A catching-up existed among several less-developed airlines, which experienced greater increase in productivity than the most efficient airlines. Multiple types of methods were used in operations to restrain CO2 emissions and flight delays. However, airline CO2 emission reduction was still inadequate to influence airline productivity during 2011-2017. All airlines should put more efforts into reducing CO2 emissions.

Although punctuality performance improved in half of the airlines, punctuality change did not facilitate overall productivity growth as expected. Market performance of the airlines did not greatly improve with flight delay reduction. Thus, the additional cost airlines have for the optimization of their punctuality performance may not always yield actual gains in productivity in the short term. However, in the long term, excellent flight punctuality would help increase customer satisfaction, attract more passengers, and reduce waste of airline resources, thus improving organization performance.

However, in the long term, excellent flight punctuality helps to increase customer satisfaction, attract more passengers, and reduce waste of airline resources, thus improving organization performance. Flight delay reduction should still be on the airlines' agendas. Given that external regulations (e.g. air traffic management) are also important factors for flight delays, the government organization should take more supportive measures to help with flight punctuality improvement.

Efficiency change and technological change were the major driving factors of airline productivity growth. Scale efficiency played an important role for both efficiency and technology change. IRS of efficiency mainly occurred in European and most of Asian airlines. Efficiency growth of North American airlines mainly originated from pure efficiency improvement, not from scale efficiency. IRS of technology only occurred in North American airlines and in part of Asian airlines. However, airlines in Europe and most of the Asian airlines had their technology progress originating from pure technology efficiency improvements. Airlines need to choose targeted operational approaches to improve their productivity.

More work should be done on this research topic. For example, more explanation factors need to be investigated on the airlines' efficiency and punctuality. Moreover, this study did not consider cost the evaluation due to data unavailability; however, this is an important factor that affects the punctuality of an airline. Further research should be on it.

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