Lecture Notes in Mechanical Engineering

Numan M. Durakbasa
M. Güneş Gençyılmaz *Editors*

# Industrial Engineering in the Industry 4.0 Era

## Selected Papers from ISPR2023, October 5–7, 2023, Antalya

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Editors

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# Efficiency Analysis of Major Airlines: Exploring the Operational Performance Determinants in Aviation

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**Abstract.** This paper evaluates the performances and dynamics of productivity changes of 38 airlines from different regions of the world between 2015 and 2019, assessing the effects of business model, alliance membership, the economic development level of the home country, and size on the operational performance of the airlines. In this regard, first, constant returns to scale (CRS) and variable returns to scale (VRS) input-oriented data envelopment analysis (DEA) models with three inputs and two outputs are implemented. The input-oriented CRS model super-efficiency DEA is also used to discriminate between efficient airlines. The Malmquist Productivity Index (MPI) estimates efficiency dynamics across time. Further, the determinants of operational efficiencies are assessed by applying Mann-Whitney rank-sum tests. The analysis results show that most airlines suffer from scale inefficiency. MPI signifies productivity deterioration in airlines' performance. It is found that low-cost carriers (LCC) have performed better than full-service carriers and alliance member airlines are less efficient than non-member airlines. Additionally, developed country airlines show better performance than their emerging country counterparts. Lastly, the size of airlines measured in available seat kilometers (ASK) is found to have no statistically significant effect on performance.

**Keywords:** Airline Alliances · Airline Efficiency · Data Envelopment Analysis · Low-Cost Carriers

## 1 Introduction

Over the past decades, with the industry's growth, airlines have faced several transformations. The restructuring of the global airline industry initially started in 1978 when the US airline industry was deregulated. In 1986, with the liberalization of the European airline industry, airlines gained the right to serve on any routes and price [1]. The liberalization has led the airlines to improve their operational efficiency in two ways [2].

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First, it gives flexibility to airlines for their network and price optimization, and hence, they improve their efficiency. Second, increased competition led by liberalization has forced airlines to operate more efficiently. Thus, airlines always have needed to gear up in this increasingly competitive area to cope with the fast changes in the industry [3]. The growing potential of the airline industry has prompted comparative analyses on airline performance. These analyses guide managers and regulatory authorities to make better decisions by increasing their awareness of the factors behind the performance.

In conjunction with these motivations, this study evaluates the performance of 38 airlines from different regions of the world between 2015 and 2019, first conducting traditional DEA and then super-efficiency DEA. The dynamics of productivity changes are also estimated utilizing MPI. Although previous studies investigated the airline performance in a variety of aspects, the potential impacts of business model, alliance membership, the economic development level of the home country, and size have not been sufficiently focused on. Therefore, this paper also enlightens to what extent these issues have an impact on the operational performance.

The rest of the paper is structured as follows: Sect. 2 reviews the literature relevant to the performance analysis of airlines. Section 3 contains the data and methodology implemented. Section 4 reveals the results and provides discussion. Section 5 concludes.

## 2 Literature Review

Various research in the literature on the evaluation of airline performance implements DEA, an appropriate tool for efficiency measurement. The DEA models used to measure the performance of airlines differ according to the aim of the research.

Chiou and Chen [4] evaluated the performance of 15 Taiwanese domestic routes by combining DEA with Tobit regression and cluster analysis. Bhadra [5] evaluated the performance of 13 US airlines between 1985 and 2006 and used Tobit regression to clarify the variations in airlines' inefficiencies. Barros and Peypoch [6] analyzed the operational performance of 29 European airlines from 2000 to 2005 and used bootstrapped truncated regression to evaluate efficiency drivers. Merkert and Williams [7] applied DEA to measure the performance of 18 European public service obligations (PSO) airlines between 2007–2009. The performances of 42 international airlines in 2006 were assessed using DEA, and the sources of efficiencies were identified with truncated regression [8]. Thirteen Indian airlines' performance between 2005 and 2012 was evaluated by Saranga and Nagpal [9]. They also utilized a two-way random effects generalized least squares regression and a Tobit model to determine efficiency drivers. The study by Choi [10] assessed DEA to measure and compare the efficiency of 14 US airlines between 2006 and 2015. The relationship between airlines' efficiency and the determinants such as international code sharing, airline size, mergers and acquisitions, and time were assessed in the study by Barros et al. [11]. Their study consists of 11 US airlines' data from 1998 to 2010 [11].

Another study proposing a different method for the performance evaluation of airlines belongs to Cui and Li [12]. They used a Virtual Frontier Benevolent DEA model to calculate the energy efficiency of 11 international airlines from 2008 to 2012 [12]. A Three-Stage Network DEA was employed to measure the efficiencies of 27 US airlines for the year 2012 [13].

Min and Joo's study is one of the few attempts to evaluate the impact of alliance membership on the performance of airlines. They evaluated the performance of 59 international airlines in 2010 concerning alliance membership [1]. A recent study questioned the impact of alliance membership on efficiency. The authors also evaluated the impact of the determinants such as freight revenue share and the continent to which airlines belong [14].

Given the overall picture of the current research, the present study contributes to the existing literature in many ways. First, it presents an extensive summary of evaluated airlines' performance and provides guidance about actions to improve efficiency. Second, it emphasizes that variations in the efficiency scores may derive from the determinants such as business model, alliance membership, the economic development level of the home country, and size. Finally, this study may also inspire further research on airline operational performance, exploring the effects of different determinants.

## 3 Methodology

The evaluation of operational performance is an important indicator to the management of the companies. The studies on the performance of airlines reveal significant results about each of the evaluated airlines and the industry. Recognizing the factors behind the efficiency/inefficiency can lead airlines to evaluate and improve their performance. Researchers have employed several methodologies to analyze the airlines' performance.

Considering the previous studies, DEA, which is a powerful non-parametric method for efficiency assessment, is determined as the method of this paper. However, traditional DEA comes with a shortcoming. The method draws an efficient frontier and designates a score of one to all efficient decision-making units (DMU). Super-efficiency DEA is also used to discriminate the performance of efficient DMUs, enabling posthoc analysis. Although DEA scores reveal the position of DMUs in the frontier for each year, the scores do not give any information about the relative position improvement or deterioration of productivity across time; thus, MPI is employed, which is an appropriate tool to measure productivity changes.

Furthermore, the effects of operational performance determinants are assessed by utilizing posthoc analysis. The main steps of the applied methodology are demonstrated in Fig. 1. The rest of this section provides summary information about the sample, data, and methodology.

### 3.1 Sample and Data

In this study, the performances of 38 airlines selected from different regions of the world between 2015 and 2019 are measured. Regarding the broad country of origin of airlines, 14 airlines are from Europe, seven airlines from North America, three from Latin America, 12 from Asia-Pacific, and two from the Middle East and Africa. The aim is to include each region's representative full-service and low-cost airlines. Of 38 airlines, 9 are LCCs from Europe, North and Latin America, and Asia-Pacific. Hence, there are 190 DMUs with 38 airline observations for five years from 2015 to 2019 (38 airlines $\times$ 5 $=$ 190 observations).

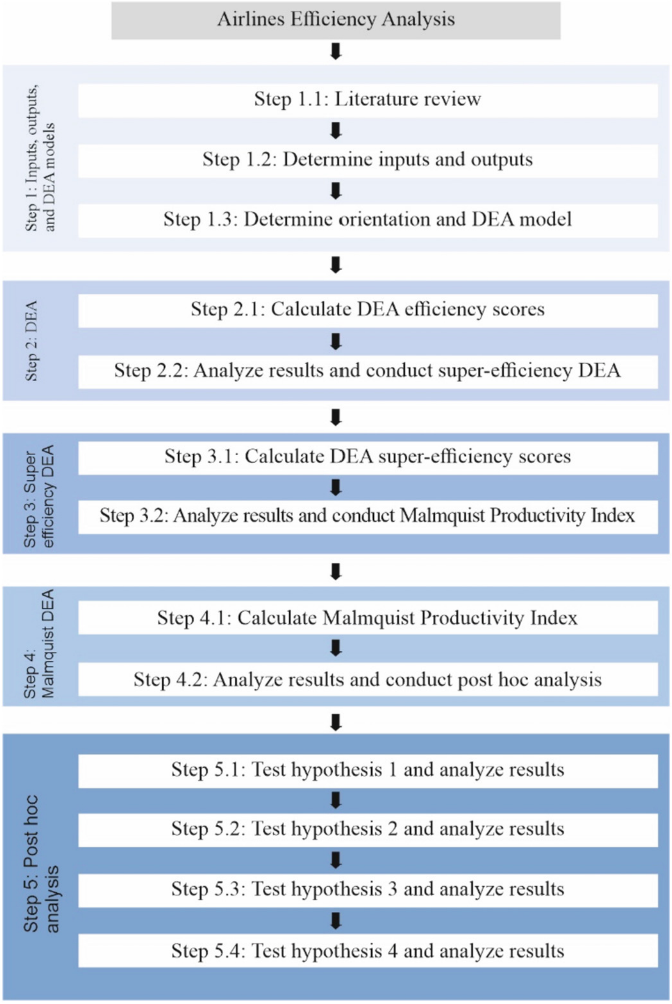

**Fig. 1.** The main steps of the recommended model

The selection of inputs and outputs is critical in DEA. In the light of the literature review of the previously conducted research and data availability, three inputs and two outputs are selected. The data set is derived from the annual reports of airlines. The inputs can be categorized as resources and expenses. The number of employees and the number of aircraft have the aspects of resources where the operating cost is under the expense category. RPK and operating revenue, which are performance indicators, are selected as outputs. RPK reflects productivity and operating income is the indicator of profitability [15].

Operating expense occurs while acquiring and utilizing the resources to perform an operation. It is a popular input measure for airline efficiency evaluation [13]. So, we use the same.

Employees are personnel involved in performing, planning, managing, and supervising the operations. The number of employees is one of the most used inputs in the literature [6, 7, 11, 12, 14–21].

Aircraft is the main means through which airline operations are conducted. Assigning the appropriate number and type of aircraft can help airlines maintain their market share and satisfy their customer needs [14]. The number of aircraft is also one of the most used inputs in the literature [6, 14, 16, 18, 20, 21].

Airlines offer passenger and freight transport services, and besides those, they have ancillary services like catering, ground handling, and maintenance. Operating revenue is the financial earnings extracted by these services. Therefore, revenue is one of the most used outputs for evaluating airline efficiencies [11, 13, 20].

RPK is the productivity indicator of an airline. It is calculated as the number of paying passengers carried on scheduled flights multiplied by the number of kilometers those seats were flown. RPK is another most widely adopted output measure [1, 6, 7, 9, 12, 14–16, 18, 21, 22].

The descriptive statistics of inputs and outputs used in the evaluation are presented in Table 1.

**Table 1.** Descriptive Statistics of the used data

| Year | | Output | | Input | | |
|---|---|---|---|---|---|---|
| | | Operating revenue (mil. USD) | RPKs (mil. Seat-kilometres) | Operating expense (mil. USD) | # of employees | # of aircrafts |
| 2015 | Mean | 11,681 | 109,407 | 10,458 | 32,370 | 335 |
| | Std. Dev. | 10,284 | 88,596 | 8,804 | 28,079 | 345 |
| 2016 | Mean | 11,466 | 114,934 | 10,257 | 33,166 | 346 |
| | Std. Dev. | 9,898 | 90,021 | 8,558 | 28,736 | 347 |
| 2017 | Mean | 12,154 | 122,781 | 11,080 | 34,126 | 357 |
| | Std. Dev. | 10,214 | 92,170 | 9,165 | 29,427 | 351 |
| 2018 | Mean | 13,271 | 130,992 | 12,255 | 35,339 | 372 |
| | Std. Dev. | 10,964 | 96,341 | 10,076 | 30,110 | 360 |
| 2019 | Mean | 13,514 | 137,244 | 12,486 | 36,438 | 380 |
| | Std. Dev. | 11,394 | 100,991 | 10,314 | 30,939 | 365 |

### 3.2 Data Envelopment Analysis (DEA)

As a non-parametric method, DEA measures the efficiency of entities known as Decision Making Units (DMUs). Without requiring any functional form on data, it enables analysis with more than one input and output [23–25]. DEA consists of different models. Constant returns to scale (CRS) and variable returns to scale (VRS) models measure the technical efficiency (TE) and pure technical efficiency (PTE) of a DMU, respectively. The ratio between TE and PTE reveals the scale efficiency (SE). DEAP Version 2 software tool is utilized to calculate the efficiency scores.

First proposed in Charnes et al. [23], a radial super-efficiency method does not change the scores of inefficient DMUs. However, it allows efficient DMUs to have scores greater than one; hence, discrimination between efficient airlines is possible. This study employs input-oriented CRS model for super-efficiency assessment of airlines using EMS Version 1.3 software tool.

Malmquist Productivity Index enables to compare the efficiency, measuring the productivity changes of a DMU over an observed time [26]. The MPI value greater than 1 indicates productivity improvement over time, but a value less than 1 implies a productivity decrease. The value 1 indicates no change in productivity. MPI consists of two components as: efficiency change (EFFCH) and technical change (TECHCH): MPI = EFFCH × TECHCH. While EFFCH represents the efficiency chance of each DMU, TECHCH represents technical change. Like MPI, a value greater than one for these two components is associated with improvement. The productivity changes of airlines in this study are calculated under input-oriented assumption by utilizing DEAP version 2 software tool.

## 4 Results and Discussion

### 4.1 DEA and Super-efficiency DEA Results

Using both CRS and VRS models enables to find airlines' TE, PTE, and SE scores.

Figure 2.a illustrates airlines' mean TE, PTE, and SE from 2015 to 2019. The highest TE mean belongs to the year 2017 with a score of 0.947. Airlines increased their average PTE scores to 0.964 in 2019, the highest average PTE score among the analyzed years. There is a decrease in average SE scores to 0.978 in 2019. The percentages of the airlines having scale efficiencies and inefficiencies each year are demonstrated in Fig. 2.b. The airlines with CRS are scale efficient, which means they have adequate dimensions for the efficiency frontier. The airlines that are too large in dimension are positioned in the frontier as DRS, and those that are too small in dimension are positioned in the frontier as IRS. The result of the analysis shows that most of the scale inefficient airlines are too large in dimension. Airlines that are too large in dimension could have improved their performance by reduction. Airlines that are too small in dimension could have improved their performance by increasing their dimensions.

In this section, super-efficiency DEA is applied under the input-oriented CRS model to determine the best-performing airline and discriminate the efficient ones. A 5-year window (2015–2019) is created by pooling all DMUs from all years to evaluate the efficiencies over a particular timeframe.

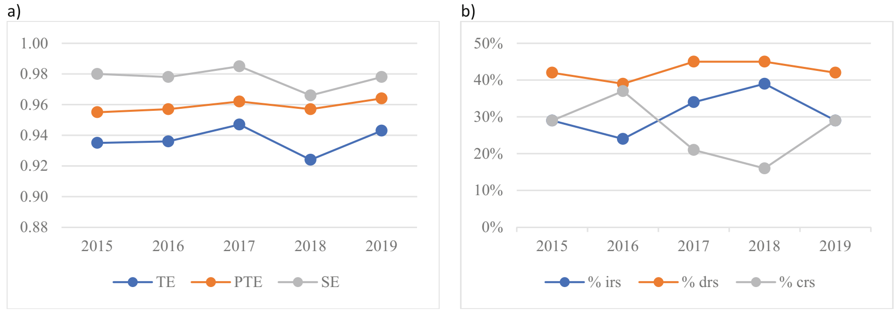

**Fig. 2.** A Mean TE, PTE and SE scores of airlines from 2015 to 2019, b. Percentage of airlines with IRS, DRS and CRS conditions

Of 190 DMUs, 44 are efficient, with scores equal to or greater than 1 (see Table 2). British Airways, Ryanair, Wizz Air, Singapore Airlines, and Emirates were efficient for all the analyzed years. The DMU reaches the highest super-efficiency score (1.386), representing Emirates for 2019. On the other hand, 0.710 is the lowest efficiency score obtained by the DMU representing Kenya Airways for 2015.

Europe and North America have been the center of aviation for decades. However, with the regional changes in economic facilities and demographics, the center of gravity has moved from west to east. As a result of this transformation, European and North American carriers have found themselves in competition with their Eastern counterparts. As proof of the competition between airlines from different regions, the Middle East and Africa is found to be the region with the highest mean efficiency score thanks to the high performance of Emirates (1.05). European airlines hold the field over their competitors (0.98), but it seems that the throne can be shaken by Asia-Pacific airlines; the mean efficiency score of airlines from Asia-Pacific (0.97) is very close to European ones. North American airlines (0.95) have lost their superiority over even Chinese and North Asian airlines (0.96). The lowest mean efficiency score belongs to the airlines from Latin America (0.87). This changing environment necessitates the implications of innovative solutions for airlines to remain competitive and efficient.

**Table 2.** Results of super-efficiency DEA by airline characteristics

| Airline | Business Model | Alliance Membership | Broad Country of Origin | Size | Year | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 2015 | 2016 | 2017 | 2018 | 2019 |
| Emirates | Full-Ser | Non-alliance | United Arab Emirates | Large | 1.291 | 1.197 | 1.299 | 1.297 | 1.386 |
| Singapore Airlines | Full-Ser | Star | Singapore | Large | 1.278 | 1.369 | 1.245 | 1.224 | 1.216 |
| British Airways | Full-Ser | Oneworld | United Kingdom | Large | 1.018 | 1.002 | 1.054 | 1.052 | 1.049 |
| Delta Arilines | Full-Ser | SkyTeam | USA | Large | 1.013 | 0.995 | 0.987 | 0.946 | 1.013 |

(*continued*)

**Table 2.** (*continued*)

| Airline | Business Model | Alliance Membership | Broad Country of Origin | Size | Year | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 2015 | 2016 | 2017 | 2018 | 2019 |
| All Nippon Airways | Full-Ser | Star | Japan | Large | 0.937 | 0.974 | 0.965 | 0.947 | 0.958 |
| United Airlines | Full-Ser | Star | USA | Large | 0.959 | 0.957 | 0.951 | 0.922 | 0.975 |
| KLM | Full-Ser | SkyTeam | Netherlands | Large | 0.923 | 0.939 | 0.975 | 0.97 | 0.953 |
| Lufthansa German Airlines | Full-Ser | Star | Germany | Large | 0.895 | 0.949 | 0.989 | 0.972 | 0.935 |
| Ryanair | Low-Cost | Non-alliance | Ireland | Large | 1.051 | 1.072 | 1.092 | 1.108 | 1.001 |
| SouthWest Airlines | Low-Cost | Non-alliance | USA | Large | 0.994 | 0.982 | 0.989 | 0.948 | 0.984 |
| Cathay Pacific | Full-Ser | Oneworld | Hong Kong | Large | 0.987 | 0.902 | 0.91 | 0.939 | 0.936 |
| Qantas | Full-Ser | Oneworld | Australia | Large | 0.925 | 0.953 | 0.932 | 0.92 | 0.933 |
| Air China | Full-Ser | Star | China | Large | 0.94 | 0.944 | 0.912 | 0.883 | 0.923 |
| Aeroflot | Full-Ser | SkyTeam | Russia | Large | 0.938 | 0.943 | 0.868 | 0.905 | 0.945 |
| Air Canada | Full-Ser | Star Alliance | Canada | Large | 0.912 | 0.908 | 0.935 | 0.898 | 0.938 |
| American Airlines | Full-Ser | OneWorld | USA | Large | 0.926 | 0.921 | 0.912 | 0.867 | 0.915 |
| Turkish Airlines | Full-Ser | Star | Turkey | Large | 0.928 | 0.829 | 0.927 | 0.932 | 0.909 |
| Air France | Full-Ser | SkyTeam | France | Large | 0.905 | 0.887 | 0.908 | 0.886 | 0.896 |
| LATAM Airlines | Full-Ser | Non-alliance | Chile | Large | 0.886 | 0.88 | 0.899 | 0.883 | 0.919 |
| China Southern Airlines | Full-Ser | Non-alliance | China | Large | 0.888 | 0.868 | 0.854 | 0.829 | 0.885 |
| China Eastern Airlines | Full-Ser | SkyTeam | China | Large | 0.872 | 0.861 | 0.836 | 0.827 | 0.871 |
| Japan Airlines | Full-Ser | Oneworld | Japan | Small | 1.001 | 1.029 | 0.982 | 0.972 | 0.984 |
| Swiss International Airlines | Full-Ser | Star | Switzerland | Small | 0.963 | 0.954 | 1.021 | 0.996 | 0.971 |
| Alaska Airlines | Full-Ser | Non-alliance | USA | Small | 1.029 | 1.01 | 0.971 | 0.872 | 0.972 |
| Eva Airways | Full-Ser | Star Alliance | Taiwan | Small | 0.959 | 0.929 | 0.99 | 0.971 | 0.974 |
| Wizz Air | Low-Cost | Non-alliance | Hungary | Small | 1.16 | 1.209 | 1.213 | 1.228 | 1.215 |
| Vueling Airlines | Low-Cost | Non-alliance | Spain | Small | 0.98 | 1.045 | 1.146 | 1.248 | 1.03 |

(*continued*)

**Table 2.** (*continued*)

| Airline | Business Model | Alliance Membership | Broad Country of Origin | Size | Year | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | 2015 | 2016 | 2017 | 2018 | 2019 |
| Air Asia | Low-Cost | Non-alliance | Malaysia | Small | 1.101 | 1.287 | 1.06 | 0.994 | 0.899 |
| Easyjet Airlines | Low-Cost | Non-alliance | United Kingdom | Small | 1.114 | 1.048 | 0.983 | 0.914 | 0.963 |
| JetBlue Airways | Low-Cost | Non-alliance | USA | Small | 1.001 | 1.011 | 0.962 | 0.853 | 0.952 |
| China Airlines | Full-Ser | SkyTeam | Taiwan | Small | 0.932 | 0.894 | 0.932 | 0.907 | 0.918 |
| Thai Airways | Full-Ser | Star | Thailand | Small | 0.918 | 0.918 | 0.971 | 0.887 | 0.885 |
| Norwegian Air Shuttle | Low-Cost | Non-alliance | Norway | Small | 0.899 | 0.923 | 0.877 | 0.88 | 0.977 |
| Scandinavian Airlines | Full-Ser | Star | Denmark-Norway-Sweden | Small | 0.881 | 0.884 | 0.921 | 0.925 | 0.92 |
| Finnair | Full-Ser | Oneworld | Finland | Small | 0.879 | 0.88 | 0.923 | 0.914 | 0.925 |
| Gol Transportes Aeros | Low-Cost | Non-alliance | Brazil | Small | 0.796 | 0.855 | 0.913 | 0.914 | 1.015 |
| Avianca | Full-Ser | Star | Colombia | Small | 0.82 | 0.846 | 0.874 | 0.846 | 0.762 |
| Kenya Airways | Full-Ser | SkyTeam | Kenya | Small | 0.71 | 0.782 | 0.955 | 0.806 | 0.846 |

## 4.2 Malmquist DEA Model Results

As aforementioned, DEA scores do not give any information about the improvements or deterioration of airline productivity. Thus, the Malmquist index is used in this study to understand whether the productivity changes of airlines are improving or worsening during the evaluated years. EFFCH scores reveal the overall efficiency change driven by managerial skills. It reflects the ability of companies to move closer or farther away from the frontier. The two components of EFFCH, PECH capture the pure managerial effect, and SECH captures the scale effect on efficiency change. TECHCH is associated with the innovation capacity of airlines [10, 19, 27].

Figure 3.a illustrates the fluctuation patterns of efficiency change, technical change, and the Malmquist index from 2015 to 2019. There are unstable oscillations of EFFCH and TECHCH scores, each index is repeatedly increasing and decreasing directly away from the other. The MPI is consistently decreasing yearly, implying a deterioration in airlines' productivity changes. The result of the analysis indicates that the driver of airlines productivity levels (either due to efficiency change or technical change) changes from year to year.

Figure 3.b illustrates the pure technical efficiency effect and scale effect on efficiency change. The fluctuation of pure efficiency change curve is stable compared to scale and efficiency change. However, an unstable oscillation of scale change has a similar pattern as efficiency change. This result indicates that EFFCH is mainly driven by scale change, implying the importance of scale optimization for efficiency improvement. This result also proves the findings of the first stage analysis.

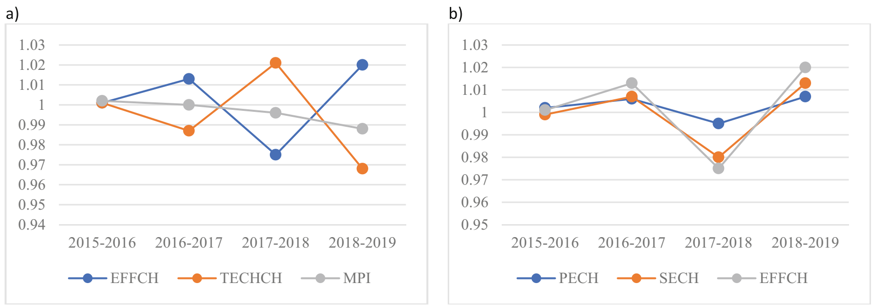

**Fig. 3.** a) Productivity changes for airlines during 2015–2019, b) The average EFFCH index and its components at annual mean over the period

## 4.3 Posthoc Analysis

Airlines have different resources, capabilities, and characteristics driven by internal and external factors. The differences in resources and capabilities may result in a competitive advantage for the airlines which perform the best [6]. In this analysis, airlines are divided into two subsets: full-service and low-cost; allied and non-allied; developed and emerging country airlines; large and small airlines to detect the effects of business model, alliance membership, economic development level of home country, and size on the operational efficiency. Accordingly, the following hypotheses are formulated.

$H_1$: Full-service airlines and low-cost airlines have identical mean efficiency.
$H_2$: Alliance member airlines and non-member airlines have identical mean efficiency.
$H_3$: Developed and emerging country airlines have identical mean efficiency.
$H_4$: Large airlines and small airlines have identical mean efficiency.

$H_1$: Low-cost and full-service airlines have distinctive characteristics. According to the acquired Z-value and p-value, which are −4.234 and 0.000, respectively, $H_1$ is rejected (see Table 3 for more details). Thus, it is assumed that there is a statistically significant mean efficiency difference between the two groups; low-cost carriers outperform full-service carriers.

$H_2$: Under the assumption that building strategic groups within an industry affects the structural characteristics of units, which can cause performance differences [28]. Thus, the sample is divided into two groups: allied and non-allied. According to the acquired Z-value and p-value, which are −5.355 and 0.000, respectively, $H_2$ is rejected (see Table 3 for further details). The mean efficiency difference between the two groups is statistically significant; non-allied airlines outperform allied airlines.

$H_3$: Except for internal factors, external factors affect a firm's performance, such as country conditions outside management's control [29]. This paper examines this argument by comparing airlines' performance in countries with different economic development stages. The level of economic development of a country is associated with its GDP. According to IMF classification, airlines' broad country of origin is labeled as developed and emerging. $H_3$ is rejected according to the acquired Z-value and p-value, which are −3.986 and 0.000, respectively (see Table 4 for more details). It is assumed that there

**Table 3.** Mann-Whitney Test results with respect to business model (H1) and alliance membership (H2)

| Group | N | Group | N |
|---|---|---|---|
| Full-service | 145 | Allied | 134 |
| Low-cost | 45 | Non-allied | 56 |
| Total | 190 | Total | 190 |
| Mann-Whitney U | 1898.00 | Mann-Whitney U | 1901.50 |
| Wilcoxon W | 12483.00 | Wilcoxon W | 10946.50 |
| Z | −4.234 | Z | −5.355 |
| p-value | 0.000 | p-value | 0.000 |

is a statistically significant mean efficiency difference between the two groups. Developed country airlines outperformed their emerging country counterparts, thus implying that the level of economic development of the home country has an impact on airlines' performance.

$H_4$: The fact that 74% of airlines under evaluation suffer from scale inefficiency necessitates analyzing the size effect on airlines' performance. Airlines are grouped as large and small according to their ASKs. ASK is a measure of capacity. Samples having $10^{11}$ or more ASKs are categorized as large, and the remaining samples are categorized as small. There are 111 samples representing large airlines and 79 samples representing small airlines. $H_4$ is not rejected according to the acquired Z-value and p-value, which are −0.031 and 0.975, respectively (see Table 4 for more details). It is assumed that there is no statistically significant mean efficiency difference between the two groups; large and small airlines operate at the same efficiency level.

**Table 4.** Mann-Whitney test results with respect to the economic development level of the home country(H3) and size of the airline (H4)

| Group | N | Group | N |
|---|---|---|---|
| Developed | 125 | Large scale | 111 |
| Emerging | 65 | Small scale | 79 |
| Total | 190 | Total | 190 |
| Mann-Whitney U | 2629.000 | Mann-Whitney U | 4373.00 |
| Wilcoxon W | 4774.000 | Wilcoxon W | 7533.00 |
| Z | −3.986 | Z | −0.031 |
| p-value | 0.000 | p-value | 0.975 |

# 5 Conclusion

This paper provides a comprehensive performance evaluation of 38 major airlines between 2015 and 2019. It contributes to the literature being one of the few attempts to assess the impacts of business model, alliance membership, the economic development level of the home country, and size on the performance. This is achieved by utilizing different DEA models and posthoc analysis.

British Airways, Ryanair, Wizz Air, Singapore Airlines, and Emirates are found to be efficient for all the analyzed years. The super-efficiency results revealed that Emirates is the most efficient airline among the evaluated airlines, with an average score of 1.29, and Kenya Airways is the least efficient airline with an average score of 0.82.

The super-efficiency analysis also lets us see different regions' mean efficiency scores. The Middle East and Africa region has the highest mean efficiency score thanks to the high performance of the Emirates. It is followed by airlines from Europe and Russia. The main competitors of European airlines are from the Asia-Pacific region, whose efficiency scores are very close to European airlines. North American airlines have lower scores than their competitors. Latin American airlines could not catch up with the frontier to be efficient and have poorer performance.

MPI shows deterioration in the productivity changes of airlines over the evaluated years, implying that the adaptation of innovative technologies by airlines is not enough for them to make a stable productivity growth. Therefore, airlines need to be concerned with innovative processes to have a competitive advantage.

The results of posthoc analysis indicate that low-cost airlines have better performance than full-service airlines.

Surprisingly, alliance membership is found to have a negative impact on the performance of airlines. Besides the internal factors, external factors such as the country conditions that the airlines operate in also impact the efficiency. Developed country airlines outperform their emerging country counterparts. On the other hand, size is found to have no impact on the performance of airlines.

This study can be extended by selecting different determinants to evaluate to what extent the airlines are sensitive to determinants. In recent years, the new trend in the airline industry has been to adopt innovative technologies to minimize operations' environmental impacts. These implications are not only beneficial for decreasing the environmental impacts but also for improving operational performance. Therefore, the relationship between environmental politics and airlines' operational performance is an attractive research topic for further studies.

Assuming that the airline industry is very fragile and sensitive to the changes, the impact of the coronavirus disease (Covid-19) pandemic is inevitable for airlines. The operational performance of airlines may be affected by this process. The impact of Covid-19 on airlines' operational performance is another topic worth further analysis.

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