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Veysi Asker
School of Civil Aviation, Dicle University, Diyarbakır, Turkey

Financial Performance Analysis Using the Merec-Based Cobra Method: An Application to Traditional and Low-Cost Airlines

Analiza wyników finansowych przy użyciu metody Cobra opartej na metodzie Merec – zastosowanie do tradycyjnych i tanich linii lotniczych

Abstract

The aim of this study is to examine the impact of the COVID-19 pandemic on the financial performance of traditional and low-cost airlines. In this context, the financial performance of 32 traditional and 14 low-cost airlines operating in different regions of the world was analysed using the Merec-based Cobra method for the before and during COVID-19 pandemic period (2018–2021). First, the financial ratios of the airlines were weighted using the Merec method, then the financial performance ranking of the airlines was conducted using the Cobra method. According to the results of the Cobra method, Ryanair (FR) was found to have the best financial performance in 2018 and 2020. Meanwhile, Allegiant Travel (G4) led the way in 2019, and Thai Airways (TG) came out on top in 2021. According to the analysis results, low-cost airlines such as Southwest Airlines (WN), Wizz Air (W6), Allegiant Air Travel (G4), and Ryanair (FR) showed better performance than a significant portion of traditional airlines in the period before the COVID- 19 pandemic. In contrast, during the COVID-19 pandemic, low-cost airlines such as Spring Airlines (9C), Air Arabia (G9), Cebu Air (5J), Easyjet (U2), and Jetblue Airways (B6) demonstrated worse performance than a significant portion of traditional airlines.

Keywords:
COVID-19 pandemic, financial performance, Merec method, Cobra method

JEL classification codes:
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Streszczenie

Celem niniejszego badania jest zbadanie wpływu pandemii COVID-19 na wyniki finansowe tradycyjnych i tanich linii lotniczych. W tym celu wyniki finansowe 32 tradycyjnych i 14 tanich linii lotniczych działających w różnych regionach świata sprzed pandemii COVID-19 i z okresu, gdy ona trwała (2018–2021), zostały przeanalizowane przy użyciu metody Cobra opartej na metodzie Merec. Najpierw wskaźniki finansowe linii lotniczych zważono, wykorzystując metodę Merec, a następnie za pomocą metody Cobra stworzono ranking wyników finansowych linii lotniczych. Zgodnie z wynikami osiągniętymi dzięki metodzie Cobra stwierdzono, że Ryanair (FR) miał najlepsze wyniki finansowe w latach 2018 i 2020. Allegiant Travel (G4) był liderem w 2019 r., a Thai Airways (TG) znalazł się na szczycie w 2021 r. Zgodnie

Słowa kluczowe:
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z wynikami analizy wyniki tanich linii lotniczych, takich jak Southwest Airlines (WN), Wizz Air (W6), Allegiant Air Travel (G4) i Ryanair (FR), były lepsze niż znacznej części tradycyjnych linii lotniczych w okresie przed pandemią COVID-19. Z kolei podczas pandemii COVID-19 tanie linie lotnicze, takie jak Spring Airlines (9C), Air Arabia (G9), Cebu Air (5J), Easyjet (U2) i Jetblue Airways (B6), osiągały wyniki gorsze niż znaczna część tradycyjnych linii lotniczych.

Introduction

The aviation sector, which holds critical importance for global markets, significantly contributes to global prosperity. In 2017, the global aviation market facilitated the transportation of $ 5.9 trillion worth of goods by air and served more than 4.1 billion passengers. Additionally, the sector provided employment to 63 million people and contributed $ 2.7 trillion to economic activities [**IATA, 2018**]. Before the outbreak of the COVID-19 pandemic in late 2019, it was estimated that the number of passengers would surpass 7 billion. However, with the onset of the COVID-19 pandemic, the global aviation market experienced a significant decline. The pandemic caused a 74% reduction in international air traffic in 2020 [**ICAO, 2022**]. It can be said that the pandemic has significantly affected the aviation sector. Airlines have implemented various strategies to mitigate these detrimental effects. These strategies include reducing or suspending flights, deferring or cancelling aircraft orders, retiring high-operating-cost aircraft and downsizing fleets, shifting focus towards cargo transportation by making changes in aircraft configuration, narrowing flight networks, and laying off employees [**Albers and Rundshagen, 2020**; **Bombelli, 2020**; **Wenzel et al., 2023**; **Czerny et al., 2021**].

Airlines are in a period where they need to reassess their business models (traditional, low-cost, charter, regional). The significant decrease in demand caused by the COVID-19 pandemic disrupted the financial structures of airline companies, and many of them required government support to sustain their operations [**Abate et al., 2020**]. However, not all airlines were equally affected by the negative impacts of the COVID- 19 pandemic. Some airlines outperformed their competitors and differentiated themselves by demonstrating better performance. For example, some airlines differed from their competitors by taking measures regarding social distance during this period [**Perez et al., 2022**]. In this regard, the main objective of this study is to investigate which business models differentiate the airlines.

We believe that this study will contribute to the literature in several ways. It provides information about the financial performance of both traditional and low-cost airlines before and during the COVID-19 pandemic. It reveals the impact of the pandemic on airline business models. It also compares the financial performance of airlines employing different business models. In the aviation industry, financial performance is considered to be as important as operational performance. However, existing studies have conducted only limited investigation into financial performance [**Asker, Aydın, 2021**; **Asker, Ustaömer, 2022**; **Kiracı, Bakır, 2020**; **Kiracı, 2019**]. We believe that our study will fill this gap in the literature. We use the Merec integrated Cobra method to analyse the financial performance of 46 airlines (32 traditional and 14 low-cost) operating in a wide geographic area during the period of 2018–2021. In the subsequent sections of the study, Section 2 reviews previous research conducted on performance measurement in airlines. Section 3 provides information about the data and methods used in the analysis. Section 4 examines the findings obtained from the analysis. Section 5 evaluates the results obtained in the research.

Literature review

Performance analysis in companies consists of a process in which data obtained from many different sources are evaluated from many angles. From this point of view, this study focuses on the financial performance analysis, which has the most impact on the overall performance of airlines. In particular, the study examines the financial performance of airlines before and during the COVID-19 period.

A significant portion of existing studies on the performance analysis of airlines has been conducted using methods such as Stochastic Frontier Analysis (SFA) [Aigner et al., 1977; Meeusen, Broeck, 1977], Total Factor Productivity Index (TFPI) [Caves et al., 1982], Data Envelopment Analysis (DEA) [Charnes et al., 1978], and Multi Criteria Decision Making (MCDM), as shown in Table 1.

Table 1. Prior studies on airline performance

Study	Period	Methods	Performance pillars	Sample size/ airlines
Hong, Zhang [2010]	1998–2002	DEA	Operational	29
Merkert, Hensher [2011]	2007–2009	Two-Stage DEA	Operational	58
Pires, Fernandes [2012]	2001–2002	TFP	Financial	42
Gramani [2012]	1997–2006	Two-Stage DEA	Financial and Operational	34
Lu et al. [2012]	2010	Two-Stage DEA	Operational	30
Hsu, Liou [2013]	2010	DEANP (Dematel and ANP]	Financial and Operational	11
Merkert, Williams [2013]	2007–2009	Two-Stage DEA	Operational	18
Lozano, Gutierrez [2014]	2007	Slack-Based DEA	Operational	16
Barros, Wanke [2015]	2010–2013	Two-Stage TOPSIS	Operational	29
Cao et al. [2015]	2005–2009	DEA and TFP	Operational	29
Omrani, Soltanzadeh [2016]	2010–2012	Dynamic DEA	Operational	8
Yu et al. [2016]	2010	DEA	Operational	13
Wang et al. [2017]	2008–2013	Dynamic DEA	Financial	49
Cui, Li [2017]	2009–2014	Dynamic DEA	Operational	19
Yu et al. [2017]	2009–2012	Dynamic Two-Stage DEA	Financial and Operational	30
Pineda et al. [2018]	2005–2014	DEMATEL, ANP, VIKOR	Financial and Operational	12
Yasar et al. [2018]	2015–2017	DEA and TFP	Operational	16
Kottas, Madas [2018]	2012–2016	DEA and Post-Hoc Analysis	Operational	30
Kiracı, Bakır [2019]	2010–2012	CRITIC, EDAS	Operational	13
Lin, Hong [2019]	2003–2012	NDEA	Financial and Operational	8
Kiracı [2019a]	1996–2015	CRITIC-Based TOPSIS	Financial	20
Kiracı [2019b]	2013–2014	MACBETH and MABAC	Financial	15
Budd et al. [2020]	2019–2020	Case Study	Financial	40
Heydari et al. [2020]	2014	Fuzzy NDEA	Operational	14
Kiracı, Yasar [2020]	1990–2017	Panel Data Analysis	Operational	52
Bakır et al. [2020]	2010–2016	PIPRECIA, MAIRCA	Operational	11
Assaf et al. [2020]	2003–2017	Bayesian SFA	Operational	11
Kiracı, Bakır [2020]	2005–2012	CRITIC, CODAS	Financial	12
Asker, Aydın [2021]	2010–2017	Tobit DEA	Financial and Operational	54
Asker [2021a]	2013–2018	Two-stage DEA	Operational and Financial	35
Atems, Yimga [2021]	2020–2021	Financial Analysis	Financial	11
Asker [2021b]	2010–2017	TFP	Financial and Operational	30
Kiracı, Asker [2021]	2018–2020	CRITIC, EDAS	Operational	6
Pereira, Melo [2021]	2019–2020	Multi-criteria DEA	Operational	3
Saini et al. [2022]	2013–2015	DEA	Operational	13
Merkert [2022]	2013–2017	Two-stage DEA	Financial and Operational	84
Asker [2022]	2016–2019	Malmquist Productivity Index	Financial	24
Mahmoudi, Emrouznejad [2022]	2013–2020	Egalitarian Bargaining Game Theory, NDEA, Malmquist Productivity Index, and SBM	Operational	12
Nguyen et al. [2022]	2015–2019	DEA-Based Meta Frontier Analysis And Truncated Regression	Financial and Operational	45
Tanriverdi, Eryaşar [2022]	2017–2020	CRITIC–CoCoSo	Operational	35

Study	Period	Methods	Performance pillars	Sample size/ airlines
Khezrimotlagh et al. [**2022**]	2005–2018	Network DEA and TFP	Operational	12
Atay et al. [**2022**]	2019–2020	DEA	Financial and Operational	10
Asker, Ustaömer [**2022**]	2016–2019	Malmquist Productivity Index	Financial	15
Kaya et al. [**2023**]	2019	Two-Stage Super-Efficiency DEA	Financial and Operational	35

Source: Author's own elaboration.

As expressed in Table 1, there are numerous studies in the literature concerning the performance analysis of airlines. Some of these studies employ DEA, some use SFA, some focus on TFP, while others utilise MCDM methods. Certain similarities and differences can be identified among these methods. For instance, while DEA involves restrictions on the number of alternatives [**Ali, See, 2023**: 3], such limitations do not apply to the SFA, TFP, and MCDM methods.

MCDM (Multi-Criteria Decision Making) methods are flexible approaches that enable the combination of qualitative and quantitative attributes. They consider the relationships between criteria, and calculate the weights of each criterion during the determination of the best decision alternative. Furthermore, within MCDM methods, weaknesses in criteria associated with each alternative can be traded off by other criteria. However, a single MCDM method that can effectively handle the process of alternative selection for all complex problems has not been developed [**Pineda et al., 2018**: 105]. Due to the lack of a valid method in the alternative selection process, alternative selections obtained as a result of MCDM models are compared with other MCDM models. The validity of the models established in this way can be tested [**Turskıs, Juodagalviene, 2016**: 1078]. MCDM models enable researchers to perform sensitivity analyses, allowing for the comparison with other MCDM methods to test the reliability and robustness of the model results [**Popoviç et al., 2022**: 67]. The MCDM models are being developed considering the shortcomings of the previously produced MCDM models. For example, the Analytical Hierarchy Process (AHP) [**Saaty, 1987**] and Best Worst Method (BWM) [**Razaei, 2015**] methods are based on a subjective assumption, while the VIKOR [**Opricovic, Tzeng, 2004**], TOPSIS [**Hwang, Yoon, 1981**], and EDAS [**Kezhavarz et al., 2015**] methods developed later are based on more objective assumptions. More recent MCDM methods are much more successful in terms of reliability and robustness [**Yalçin et al., 2022**: 2]. In this context, the Method Based on the Removal Effects of Criteria – MEREC [**Keshavarz-Ghorabae et al., 2021**] and the Comprehensive Distance-Based Ranking – COBRA [**Krstic et al., 2022**], which are the most recent MCDM methods, are applied in the study. To increase the reliability and robustness of the results, we compared the results of two methods with other MCDM methods (Marcos [**Steviç et al., 2020**], Mairca [**Gigoviç et al., 2016**], and Edas [**Kezhavarz et al., 2015**]).

Despite the existence of numerous studies that examine airlines using MCDM methods, it has been observed that these studies cover a limited number of airlines and predominantly focus on operational performance [**Barros, Wanke, 2015**; **Pineda et al., 2018**; **Kiracı, Bakır, 2019**; **Bakır et al., 2020**; **Kiracı, Asker, 2021**; **Tanrıverdi, Eryaşar, 2022**]. However, the number of studies examining financial performance is quite limited [**Kiracı, 2019**; **Kiracı, Bakır, 2020**]. We believe that this study will contribute to the literature in several aspects. First, it comprehensively examines the financial sustainability of airlines by comparing the financial performance of globally recognised airlines. Second, it investigates how traditional and low-cost airlines were affected by the crisis resulting from the COVID-19 pandemic.

Data and methodology

In this study, we examine the financial performance of a total of 46 airline companies, including 32 traditional and 14 low-cost airlines, during the period of 2018–2021. We focus on nine criteria and analyse the financial performance of the airlines using the Merec [**Keshavarz-Ghorabae et al., 2021**] and Cobra [**Krstic et al., 2022**] methods. The financial performance criteria included in the study are presented in Table 2.

Table 2. Performance criteria and codes

Performance Criteria	Type	Code	References
Liquid Assets / Short-Term Liabilities	Max	C1	Kiracı, Bakır [2020]
Total Debt / Total Assets	Min	C2	Jandghi, Ramshini [2014]
Net Profit / Net Sales	Max	C3	Asker, Aydın [2021], Asker [2021]
Net Profit / Total Assets	Max	C4	Pires, Fernandes [2012]
Gross Profit / Net Sales	Max	C5	Kiracı et al. [2022]
Total Debt / Equity	Min	C6	Wang et al. [2017]
Net Profit / Equity	Max	C7	Pineda et al. [2018]
Operating Income/ Total Asset	Max	C8	Kaya et al. [2023]
Operating Income / Equity	Max	C9	Kottas, Madas [2018]

Source: Author's own elaboration.

The variables presented in Table 2 have been chosen among the most commonly used variables in studies related to performance measurement in airlines. Additionally, we conducted the Spearman correlation to ascertain the strength and direction of the relationship between these variables. We determined that there is no problematic correlation among the performance criteria. The results of the Spearman correlation for the performance criteria are shown in Table 3.

Table 3. Spearman correlation coefficient of performance criteria

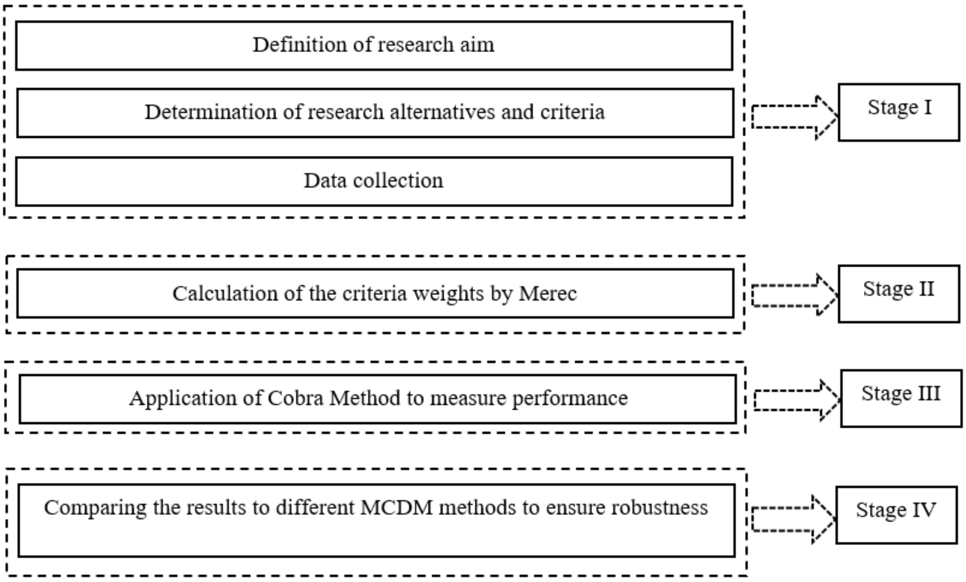
	C1	C2	C3	C4	C5	C6	C7	C8	C9
C1	1	−0.6289	0.2663	−0.0165	0.2401	−0.0628	−0.2404	0.4133	0.0382
C2	−0.6289	1	−0.4513	−0.3199	−0.3773	0.0554	0.3364	−0.3492	0.2683
C3	0.2663	−0.4513	1	0.7021	0.9824	0.2842	−0.4022	−0.1025	−0.3742
C4	−0.0165	−0.3199	0.7021	1	0.6265	0.2578	−0.2075	−0.6071	−0.5277
C5	0.2401	−0.3773	0.9824	0.6265	1	0.2749	−0.3686	−0.0501	−0.3040
C6	−0.0628	0.0554	0.2842	0.2578	0.2749	1	−0.8197	−0.0780	−0.5872
C7	−0.2404	0.3364	−0.4022	−0.2075	−0.3686	−0.8197	1	−0.1530	0.6795
C8	0.4133	−0.3492	−0.1025	−0.6071	−0.0501	−0.0780	−0.1530	1	0.3566
C9	0.0382	0.2683	−0.3742	−0.5277	−0.3040	−0.5872	0.6795	0.3566	1

Source: Author's own calculation.

The data on the airlines has been collected from the Bloomberg database, which offers services through a paid subscription model (https://www.bloomberg.com/professional/product/research/), as well as from annual reports published by the airlines.

Figure 1 shows the Merec-based Cobra method used in the study. In the first step, the criteria related to the research problem are determined, and then data related to the criteria are collected. In the second step, the Merec method is used to determine the weights of the performance criteria. In the third step, the financial performance of airlines is calculated and ranked for each year using the Cobra method. In the last step, the validity and reliability of the proposed model have been increased by comparing the sorting results obtained as a result of the analysis with similar MCDM methods (Marcos, Mairca, Edas).

Figure 1. Flow chart of the application model



Source: Author's own elaboration.

Merec criteria weighting method

The Merec method [**Keshavarz-Ghorabae et al., 2021**] is an objective weighting model. In the Merec method, when calculating the criterion weights, the criterion in question is not taken into account and then the change in the total criterion weight is measured. The criterion that causes the most change in the total criterion weight is considered the most important one. This feature distinguishes the Merec method from other objective weighting methods (ENTROPY, CRITIC, CILOS) [**Haq et al., 2022**]. The Merec method has an application process consisting of six stages. The application steps of the method are shown below [**Keshavarz-Ghorabae et al., 2021**].

Step 1: Define a Decision Matrix: The decision matrix consisting of n criteria and m alternatives is formed as shown in Equation (1).

$$A = \begin{bmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{bmatrix}, \quad \begin{matrix} i = 1, \ldots, m \\ j = 1, \ldots, n \end{matrix} \tag{1}$$

The elements of the decision matrix showing the values taken by the alternative "i" belonging to the criterion "J" should take positive values. If there are negative values in the decision matrix, these data should be converted into positive values by appropriate methods.

Step 2: *Normalisation of the Decision Matrix*: In the second step of the method, the relevant criteria are normalised with the help of Equation (2) according to their beneficial and non- beneficial directional status.

$$n_{ij} = \begin{cases} \dfrac{\min\limits_i x_{ij}}{x_{ij}}, & j \in \mathrm{B} \\ \dfrac{\max\limits_i x_{ij}}{x_{ij}}, & j \in \mathrm{H} \end{cases} \tag{2}$$

If "B" represents the set of beneficial criteria, "H" shows the set of non-beneficial criteria.

Step 3: Calculation of the Overall Performance Values of Alternatives: The overall performance values (S_i) of the alternatives are calculated using Equation (3).

$$S_i = \ln\left(1+\left(\frac{1}{n}\sum_j \left|\ln(n_{ij})\right|\right)\right) \tag{3}$$

Step 4: Calculation of the Overall Performance Value (S'_{ij}) by Subtracting the Values of Each Criterion from the Decision Matrix: In this step, a logarithmic criterion is used as in the previous step. The main difference between this step and Step 3 is the calculation of the performance of decision alternatives separately for each criterion. The overall performance of alternative "i" with the exclusion of criterion "J" is denoted as S'_{ij}. Overall performance value (S'_{ij}) is calculated by using Equation (4).

$$S'_{ij} = \ln\left(1+\left(\frac{1}{n}\sum_{k,k\neq j} \left|\ln(n_{ij})\right|\right)\right) \tag{4}$$

Step 5: Calculation of the Total Value of Absolute Deviations (Ej): We determine the sum of absolute deviations (Ej) by employing Equation (5).

$$E_j = \sum_i \left|S'_{ij} - S_i\right| \tag{5}$$

Step 6: Calculation of the Importance Weight of Each Criterion: In the last step of the method, the importance weights of the relevant criteria are calculated with the help of Equation (6).

$$w_j = \frac{E_j}{\sum_k E_k} \tag{6}$$

Cobra ranking method

Krstic et al. [2022] developed the Cobra (Comprehensive Distance Based Ranking) method. The Cobra method is a newly developed MCDM method that has been used in very few studies so far [Krstic et al., 2022; Popovic et al., 2022]. The application steps of the Cobra method are shown below [Krstic et al., 2022]:

Step 1: Define a decision matrix consisting of evaluation criteria and decision alternatives as shown in Equation (1).

Step 2: Create the normalised decision matrix as shown in Equation (7) and Equation (8).

$$\Delta = [\alpha_{ij}]_{nm} \tag{7}$$

$$\alpha_{ij} = \frac{\alpha_{ij}}{max_i a_{ij}} \tag{8}$$

Step 3: Create the weighted normalised decision matrix by using Equation (9). The value of "w_j" is the weight value of each criterion obtained as a result of the Merec method.

$$\Delta_w = \left[\omega_j \times \alpha_{ij}\right]_{n\times m} \tag{9}$$

Step 4: Define Negative ideal (NIS_j), Positive ideal (PIS_j), and average solution (AS_j) for each criterion function by using Equation (10–14).

$$PIS_j = max_i(\omega_j \times \alpha_{ij}), \quad \forall_j = 1,......m \quad za \quad j \ni J^B \tag{10}$$

$$PIS_j = min_i(\omega_j \times \alpha_{ij}), \quad \forall_j = 1,......m \quad za \quad j \ni J^C \tag{11}$$

$$NIS_j = min_i(\omega_j \times \alpha_{ij}), \quad \forall_j = 1,......m \quad za \quad j \ni J^B \tag{12}$$

$$NIS_j = max_i(\omega_j \times \alpha_{ij}), \quad \forall_j = 1,......m \quad za \quad j \ni J^C \tag{13}$$

$$AS_j = \frac{\sum_{i=1}^{n}(\omega_j \times \alpha_{ij})}{n} \quad \forall_j = 1,......m \quad za \quad j \ni J^B, J^C \tag{14}$$

"J^B" is the set of benefit and "J^C" is the set of cost criteria.

Step 5: We define both the negative ideal solution ($d(NIS_j)$) and the positive ideal solution ($d(PIS_j)$) for each alternative. Additionally, we calculate the positive ($d(AS_j)_i^+$) and negative ($d(AS_j)_i^-$) distances from the average solution values using Equation (15).

$$d(S_j) = dE(S_j) + \partial \times dE(S_j) \times dT(S_j) \quad \forall_j = 1,......m, \tag{15}$$

where "S_j" shows any solution (NIS_j, PIS_j, AS_j), "∂" is the correction coefficient calculated as follows:

$$\partial = max_i dE(S_j) - min_i dE(S_j), \tag{16}$$

The values of $dE(S_j)$ and $dT(S_j)$ represent the Euclidian and Taxicab distances respectively, which are calculated for the positive ideal solution. They are calculated by using Equation (17) and Equation (18).

$$dE(PIS_j)_i = \sqrt{\sum_{j=1}^{m}\left(PIS_j - \omega_j \times \alpha_{ij}\right)^2} \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{17}$$

$$dT(PIS_j)_i = \sum_{j=1}^{m}\left|PIS_j - \omega_j \times \alpha_{ij}\right| \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{18}$$

For the negative ideal solution, Euclidean and Taxicab distances are calculated using Equation (19) and Equation (20) respectively.

$$dE(NIS_j)_i = \sqrt{\sum_{j=1}^{m}\left(NIS_j - \omega_j \times \alpha_{ij}\right)^2} \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{19}$$

$$dT(NIS_j)_i = \sum_{j=1}^{m}\left|NIS_j - \omega_j \times \alpha_{ij}\right| \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{20}$$

For the positive distance from the average solution, Euclidean and Taxicab distances are calculated using Equations (21–23) respectively.

$$dE(AS_j)_i^+ = \sqrt{\sum_{j=1}^{m}\tau^+\left(AS_j - \omega_j \times \alpha_{ij}\right)^2} \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{21}$$

$$dT(AS_j)_i^+ = \sum_{j=1}^{m}\tau^+\left|AS_j - \omega_j \times \alpha_{ij}\right| \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{22}$$

$$\tau^+ = \begin{cases} 1 & if \quad AS_j < \omega_j \times \alpha_{ij} \\ 0 & if \quad AS_j > \omega_j \times \alpha_{ij} \end{cases}, \tag{23}$$

For the negative distance from the average solution, Euclidean and Taxicab distances are calculated using Equations (24–26) respectively.

$$dE(AS_j)_i^- = \sqrt{\sum_{j=1}^{m}\tau^-\left(AS_j - \omega_j \times \alpha_{ij}\right)^2} \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{24}$$

$$dT\,dT(AS_j)_i^- = \sum_{j=1}^{m}\tau^-\left|AS_j - \omega_j \times \alpha_{ij}\right| \quad \forall_i = 1,......,n, \quad \forall_j = 1,......,m, \tag{25}$$

$$\tau^{-} = \begin{cases} 1 \;\; if \;\; AS_j > \omega_j \times \alpha_{ij} \\ 0 \;\; if \;\; AS_j < \omega_j \times \alpha_{ij} \end{cases}, \tag{26}$$

Step 6: Rank the considered alternatives in ascending order based on the comprehensive distances by using Equation (27).

$$dC_i = \frac{d(PIS_j)_i - dE(NIS_j)_i - d(AS_j)_i^{+} + dT(AS_j)_i^{-}}{4} \quad \forall_i = 1, \ldots\ldots, n, \tag{27}$$

Results

In this section, we examined the financial performance of traditional and low-cost airlines before and during the COVID-19 pandemic using the Merec-based Cobra method. To enhance the validity and reliability of the proposed model, we compared the results obtained with popular MCDM models (Marcos, Mairca, and Edas). The research covered the financial performance of 46 airlines for the period of 2018–2021. In order to save space, the two-letter codes provided by the International Air Transport Association (IATA) were used instead of the names of the airlines. The airlines included in the research are listed in the appendix, along with the two-letter IATA codes assigned by IATA.

Merec result

At this stage, the weights of the criteria included in the initial decision matrix for airlines were determined using the Merec method. The Decision Matrix consists of financial data for each airline for each year. Since data for 46 airlines over four years were used in this study, a decision matrix of size 46 × 4 has been created s. Looking at Table 4, we can see the weights of financial criteria for the 2018–2021 period. According to Table 4, Total Debt / Total Assets (C2) is observed to be the variable with the highest weight. In this context, foreign resource utilisation (Total Debt / Total Assets Rate) is identified as the variable with the highest weight both in the period before the COVID-19 pandemic (2018–2019) and during the COVID-19 pandemic (2020–2021).

Table 4. Merec method performance criteria weight, 2018–2021

Year	C1	C2	C3	C4	C5	C6	C7	C8	C9
2018–2021	0,1140	**0,2320**	0,1120	0,1118	0,0838	0,0850	0,0935	0,0925	0,0758

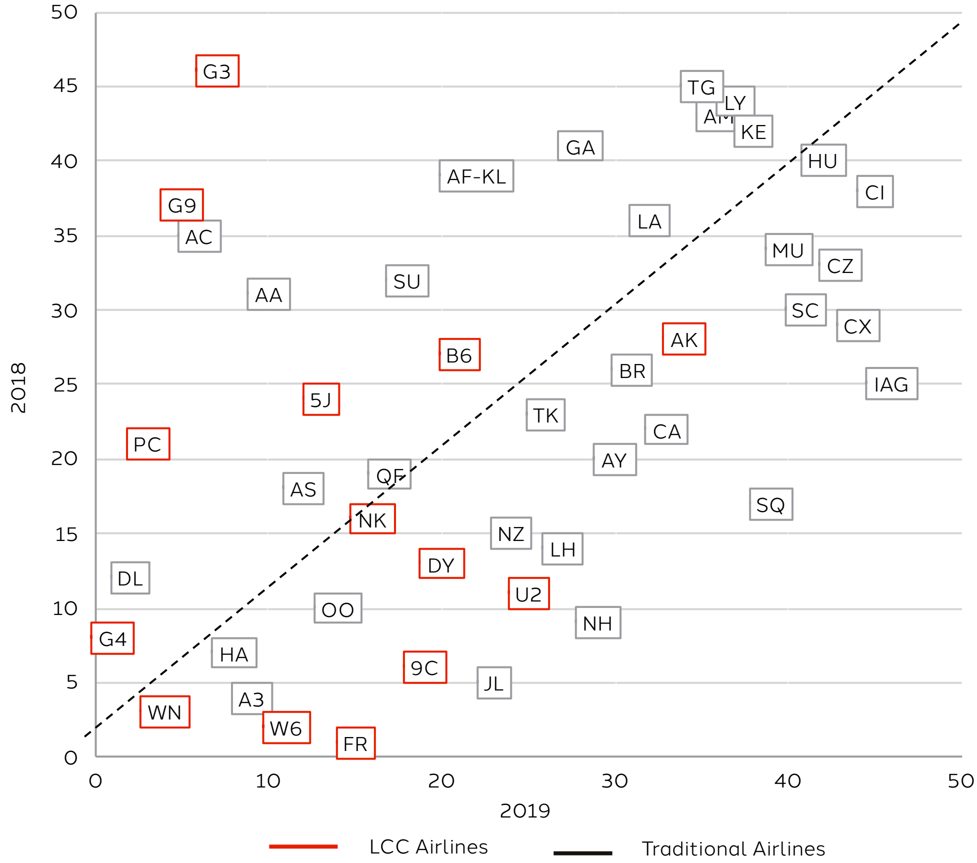
Source: Author's own calculation.

Cobra ranking result

After determining the airline criteria weights with the Merec method, we examined the performances of traditional and low-cost airlines using the Cobra method. In the first stage, we compared the performance rankings of traditional and low-cost airlines in 2018 and 2019 (pre-COVID-19 period) using the Cobra method. As shown in Figure 2, according to the Cobra method's ranking results for 2018, Ryanair (FR) showed the best performance, while Gol Linhas (G3) showed the worst performance. In the ranking results for 2019, Allegiant Air Travel (G4) showed the best performance, while International Airlines Group (IAG) showed the worst performance. Southwest Airlines (WN), Wizz Air (W6), Allegiant Air Travel (G4), Hawaiian Airlines (HA), and Aegean Airlines (A3) ranked relatively high in terms of financial performance in both 2018 and 2019. On the other hand, China Airlines (CI), Hainan Airlines (HU), and Korean Airlines (KE) were found at the bottom of the rankings in both 2018 and 2019.

Low-cost airlines such as Southwest Airlines (WN), Wizz Air (W6), Allegiant Air Travel (G4), and Ryanair (FR) showed better performance in 2018 and 2019 than a significant portion of traditional airlines. Low-cost airlines are those that have only narrow-body aircraft in their fleet, operate to secondary airports, offer paid in-flight services, and have short turnaround times. Low-cost airlines are able to reduce their operating costs significantly thanks to these characteristics. This explains the better financial performance of some low-cost airlines included in our study in 2018 and 2019.

Figure 2. Performance ranking of airlines according to the Cobra method, 2018–2019



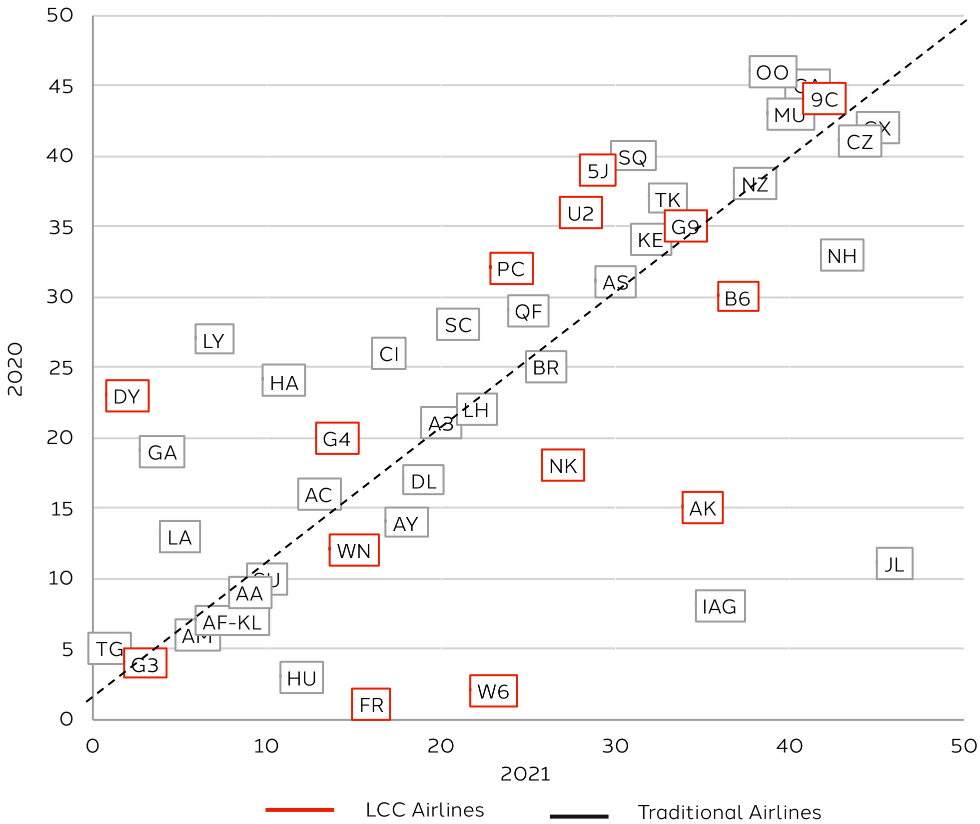
Source: Author's own calculation.

In the second stage of the analysis, we compared the performance rankings of traditional and low-cost airlines in 2020 and 2021 (COVID-19 pandemic period) using the Cobra method. As shown in Figure 3, according to the Cobra method's ranking results for 2020, Ryanair (FR) exhibited the best performance, while Skywest (OO) showed the worst performance. In the ranking results for 2021, Thai Airways (TG) displayed the best performance, while Japan Airlines (JL) showed the worst performance. Thai Airways (TG), Gol Linhas (G3), Aeromexico (AM), Air France-KLM (AF-KL), and American Airlines (AA) ranked relatively high in terms of financial performance in both 2020 and 2021. On the other hand, Cathay Pacific Air (CX), Skywest (OO), Air China (CA), Spring Airlines (9C), and China Eastern Airlines (MU) ranked at the bottom of the list in both 2020 and 2021.

It has been observed that low-cost airlines such as Spring Airlines (9C), Air Arabia (G9), Cebu Air (5J), Easyjet (U2), and Jetblue Airways (B6) ranked at the bottom in terms of financial performance in 2020 and 2021. Among the possible reasons for this, it can be pointed out that traditional airlines modified large passenger aircraft for cargo transportation during the COVID-19 pandemic, while LCC airlines, due to having smaller aircraft, were unable to engage in cargo transportation [Jaroenjitrkam et al., 2023].

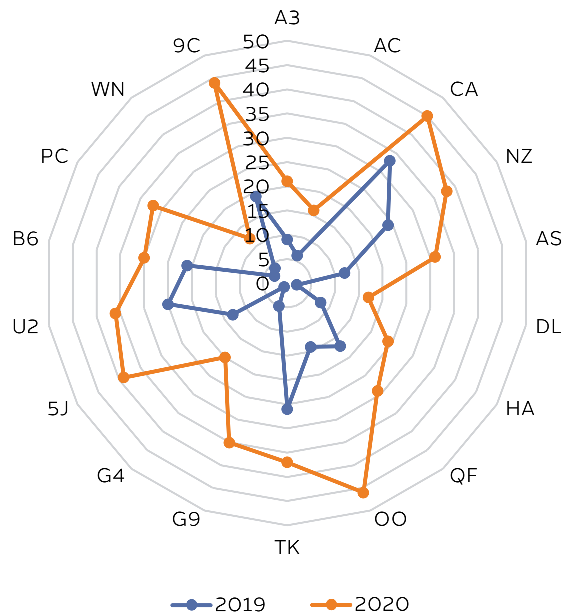
According to the results of the Cobra method for 2020 and 2021, it has been observed that large-scale traditional airlines such as China Eastern Airlines (MU) and China Southern Airlines (CZ) showed worse performance than medium-sized traditional airlines such as Hainan Airlines (HU) and Hawaiian Airlines (HA), as well as small-scale traditional airlines such as Eva Airways (BR) and Finnair (AY). This can be explained by the impact of international travel restrictions imposed during the COVID-19 pandemic, which affected large-scale traditional airlines with extensive international flight networks to a greater extent.

Figure 3. Performance ranking of airlines according to the Cobra method, 2020–2021



Source: Author's own calculation.

Figure 4. Performance ranking of some airlines according to the Cobra method, 2019–2020

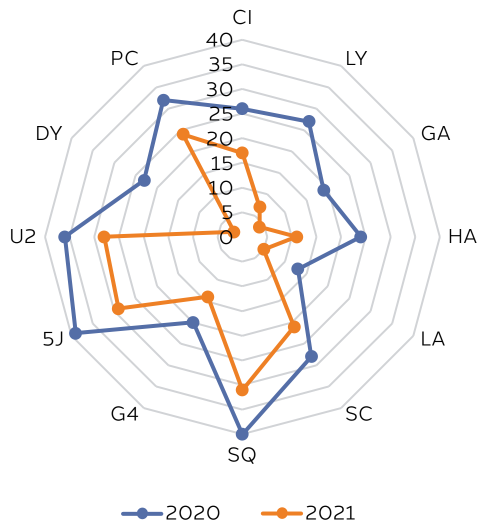


Source: Author's own calculation.

According to the ranking results obtained from the Cobra method, as shown in Figure 4, it has been observed that airlines such as Aegean Airlines (A3), Air Canada (AC), Air China (CA), Air New Zealand (NZ), Alaska Airlines (AS), Delta Airlines (DL), Hawaiian Airlines (HA), Qantas Airways (QF), Skywest (OO), Turkish Airlines (TK), Air Arabia (G9), Allegiant Travel (G4), Cebu Air (5J), Easyjet (U2), Jetblue Airways (B6), Pegasus (PC), Southwest Airlines (WN), and Spring Airlines (9C) experienced a decline in their performance rankings in 2020 compared to 2019. This may have been due to decreased operational revenues and a deterioration in liquidity for these airlines.

According to the findings obtained as a result of the analysis, as shown in Figure 5, it has been observed that airlines such as China Airlines (CI), El Al İsrael Airlines (LY), Garuda Indonesia (GA), Hawaiian Airlines (HA), Latam Airlines (LA), Shandong Airlines (SC), Singapore Airlines (SQ), Allegiant Travel (G4), Cebu Air (5J), Easyjet (U2), Norwegian Air (DY) and Pegasus (PC) showed relative improvements in their performance rankings in 2021 compared to the previous year. This can be explained by the partial lifting of travel restrictions and the financial support provided by governments in 2021.

Figure 5. Performance ranking of some airlines according to the Cobra method, 2020–2021



Source: Author's own calculation.

Validation

To test the validity of the applied model, we compared the ranking results obtained through the Cobra method with other popular MCDM (Multiple Criteria Decision Making) methods such as Marcos, Mairca, and Edas. In this context, the Marcos, Mairca, and Edas methods were applied to the existing sample and data for 2018. Subsequently, the ranking results for airlines for 2018 were obtained according to all MCDM methods. The ranking results obtained from the analysis conducted for all MCDM methods are presented in Table 5.

Table 5. Airlines ranking results for each comparison method, 2018

Airlines	IATA Code	Cobra	Marcos	Mairca	Edas
Aegean Airlines	A3	4	11	15	14
Aeroflot	SU	32	29	43	28
Aeromexico	AM	43	35	35	30
Air Canada	AC	35	30	22	24
Air China	CA	22	44	39	39
Air France – KLM	AF-KL	39	32	34	43
Air New Zealand	NZ	15	23	18	5

Airlines	IATA Code	Cobra	Marcos	Mairca	Edas
Alaska Airlines	AS	18	26	32	29
American Airlines	AA	31	17	11	18
All Nippon Airways	NH	9	5	8	6
Cathay Pacific Air	CX	29	37	29	32
China Airlines	CI	38	38	38	38
China Eastern Airlines	MU	34	18	33	37
China Southern Airlines	CZ	33	16	31	35
Delta Airlines	DL	12	7	9	10
El Al Israel Airlines	LY	44	46	45	45
Eva Airways	BR	26	25	26	25
Finnair	AY	20	9	20	20
Garuda Indonesia	GA	41	33	41	42
Hainan Airlines	HU	40	43	40	41
Hawaiian Airlines	HA	7	21	6	7
International Airlines Group	IAG	25	28	25	26
Japan Airlines	JL	5	14	5	11
Korean Airlines	KE	42	34	42	40
Latam Airlines	LA	36	42	37	36
Lufthansa	LH	14	13	14	16
Qantas Airways	QF	19	10	16	15
Shandong Airlines	SC	30	31	30	33
Singapore Airlines	SQ	17	6	17	21
Skywest	OO	10	12	13	12
Thai Airways	TG	45	45	44	44
Turkish Airlines	TK	23	36	23	22
Air Arabia	G9	37	39	36	34
Airasia	AK	28	41	28	31
Allegiant Travel	G4	8	15	10	9
Cebu Air	5J	24	24	24	23
Easyjet	U2	11	22	12	13
Gol Linhas	G3	46	40	46	46
Jetblue Airways	B6	27	27	27	27
Norwegian Air	DY	13	**1**	3	**1**
Pegasus	PC	21	19	21	19
Ryanair	FR	**1**	2	2	3
Southwest Airlines	WN	3	4	4	4
Spirit Air	NK	16	20	19	17
Spring Airlines	9C	6	8	7	8
Wizz Air	W6	2	3	**1**	2

Source: Author's own calculation.

As shown in Table 5, Ryanair, Wizz Air and Norwegian Air have been identified as exhibiting the best financial performance during 2018 according to four different MCDM methods. Although there were minor differences, it has been observed that similar rankings were generated across four different methods. These results support the validity of the proposed model and demonstrate the high compatibility of the Cobra method with other MCDM methods. Furthermore, to increase the consistency of the proposed model and to determine the strength and direction of the relationship between the results obtained from the four different MCDM models, we conducted the Spearman correlation analysis. The results of the Spearman correlation for the respective methods are shown in Table 6.

Table 6. Spearman correlation coefficient of different MCDM methods results

	Cobra	Marcos	Mairca	Edas
Cobra	1	0.8047	0.9044	0.9127
Marcos	0.8047	1	0.8635	0.8429
Mairca	0.9044	0.8635	1	0.9357
Edas	0.9127	0.8429	0.9357	1

Source: Author's own calculation.

When examining the correlation results in Table 6, we observed a high positive correlation among the MCDM methods. This finding supports the validity and consistency of the results obtained from the proposed Cobra method.

Conclusion

The travel restrictions imposed during the COVID-19 pandemic had a negative impact on the aviation sector. This led to a decrease in demand for airlines and a reduction in their revenue sources. As a result, many airlines faced financial difficulties and were at risk of bankruptcy. Consequently, numerous airlines made decisions such as postponing or cancelling aircraft orders, disposing of high-cost aircraft, reducing employee wages, or laying off employees. However, the effects of these decisions are not fully understood. Therefore, it is crucial to investigate the adverse effects of the COVID-19 pandemic on airlines. This study examined the financial performance of traditional and low-cost airlines before and during the COVID-19 pandemic using Merec-based Cobra methods.

In the first step of the analysis, the weights of financial ratios were calculated using the Merec method. According to the results of the Merec method, it can be said that foreign resource utilisation (Total Debt / Total Assets Rate) carried more weight on the financial performance of traditional and low-cost airlines before and during the COVID-19 pandemic. In the second step of the analysis, the performance rankings of traditional and low-cost airlines were conducted using the Cobra method. According to the results of the Cobra method, Ryanair (FR) was found to have the best financial performance in 2018 and 2020. Meanwhile, Allegiant Travel (G4) led the way in 2019, and Thai Airways (TG) came out on top in 2021.

The results of the proposed Merec-based Cobra model reflect the comprehensive performance rankings of the included airlines for each separate year from 2018 to 2021. Additionally, it demonstrates that there were differences in the relative financial performance of traditional and low-cost airlines before and during the COVID-19 pandemic. Low-cost airlines such as Southwest Airlines (WN), Wizz Air (W6), Allegiant Air Travel (G4), and Ryanair (FR) showed better performance than a significant portion of traditional airlines in the period before the COVID-19 pandemic. Among the possible reasons for this is the successful implementation of cost-cutting practices by low-cost airlines before the COVID-19 pandemic, such as using secondary airports and offering paid in-flight services. During the COVID-19 pandemic, however, low-cost airlines such as Spring Airlines (9C), Air Arabia (G9), Cebu Air (5J), Easyjet (U2), and Jetblue Airways (B6) performed worse than a significant portion of traditional airlines. This may have been because traditional airlines modified large passenger aircraft for cargo transportation during the COVID-19 pandemic, while LCC airlines, which rely on smaller aircraft, were unable to engage in cargo transportation [**Jaroenjitrkam et al., 2023**].

According to the results of the Merec-based Cobra model, traditional airlines such as Aegean Airlines (A3), Air Canada (AC), Air China (CA), Air New Zealand (NZ), Alaska Airlines (AS), Delta Airlines (DL), Hawaiian Airlines (HA), Qantas Airways (QF), Skywest (OO), and Turkish Airlines (TK) experienced a decline in their performance rankings in 2020 compared to 2019. A similar situation was observed in low-cost airlines such as Air Arabia (G9), Allegiant Travel (G4), Cebu Air (5J), Easyjet (U2), Jetblue Airways (B6), Pegasus (PC), Southwest Airlines (WN), and Spring Airlines (9C). Possible reasons for this may include a decrease in operational revenues and a deterioration in liquidity for these airlines in 2020.

According to the analysis findings, traditional airlines such as China Airlines (CI), El Al Israel Airlines (LY), Garuda Indonesia (GA), Hawaiian Airlines (HA), Latam Airlines (LA), Shandong Airlines (SC), and Singapore Airlines (SQ) showed relative improvements in their performance rankings in 2021 compared to the previous year. A similar situation was observed in low-cost airlines such as Allegiant Travel (G4), Cebu Air (5J), Easyjet (U2), Norwegian Air (DY), and Pegasus (PC). This can be explained by the partial lifting of travel restrictions and the financial support provided by governments in 2021.

According to the analysis results, large-scale traditional airlines such as China Eastern Airlines (MU) and China Southern Airlines (CZ) demonstrated worse performance during the COVID-19 pandemic (2020–2021) than medium-sized traditional airlines such as Hainan Airlines (HU) and Hawaiian Airlines (HA), as well as small-scale traditional airlines such as Eva Airways (BR) and Finnair (AY). This can be explained by the impact of international travel restrictions imposed during the COVID-19 pandemic, which affected large-scale traditional airlines with extensive international flight networks to a greater extent.

It is believed that this study, which used the Merec-based Cobra method, will contribute to the rapidly growing literature on Multiple Criteria Decision Making (MCDM). Additionally, it provides information to stakeholders in the aviation industry about the financial performance of airlines during the COVID-19 pandemic. However, there are some limitations to our study. These include the sampling of only passenger airlines and the examination of performance solely from a financial perspective. However, depending on the selected criteria, the performance ranking can vary. In future studies, the operational, environmental, and sustainability performance of traditional and low-cost airlines during the COVID-19 pandemic could be examined.

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Appendix

Traditional Airlines	IATA Code	Low-Cost Airlines	IATA Code
Aegean Airlines	A3	Air Arabia	G9
Aeroflot	SU	Airasia	AK
Aeromexico	AM	Allegiant Travel	G4
Air Canada	AC	Cebu Air	5J
Air China	CA	Easyjet	U2
Air France – KLM	AF-KL	Gol Linhas	G3
Air New Zealand	NZ	Jetblue Airways	B6
Alaska Airlines	AS	Norwegian Air	DY
American Airlines	AA	Pegasus	PC
All Nippon Airways	NH	Ryanair	FR
Cathay Pacific Air	CX	Southwest Airlines	WN
China Airlines	CI	Spirit Air	NK
China Eastern Airlines	MU	Spring Airlines	9C
China Southern Airlines	CZ	Wizz Air	W6
Delta Airlines	DL		
El Al Israel Airlines	LY		
Eva Airways	BR		
Finnair	AY		
Garuda Indonesia	GA		
Hainan Airlines	HU		
Hawaiian Airlines	HA		
International Airlines Group	IAG		
Japan Airlines	JL		
Korean Airlines	KE		
Latam Airlines	LA		
Lufthansa	LH		
Qantas Airways	QF		
Shandong Airlines	SC		
Singapore Airlines	SQ		
Skywest	OO		
Thai Airways	TG		
Turkish Airlines	TK		

Source: International Air Transport Association (IATA) and airlines' annual report.