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Financial Efficiency in Airlines During the COVID-19 Pandemic: A DEA Approach

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Abstract The airline industry is a competitive sector in which most airline companies face challenges in retaining passengers and achieving sustainable profitability. To survive in this competitive environment, an airline must be able to offer and sell more air services while using fewer resources. Under the strain of the COVID-19 pandemic, airlines have pivoted toward strategies that optimize their resource usage to develop competitive strategies centered on enhancing their efficiency. Considering this, the present study seeks to evaluate and contrast the efficiency levels of 19 prominent airline carriers, all affiliated with the International Air Transport Association (IATA), during the period spanning 2017 to 2021. Employing the methodologies of Data Envelopment Analysis (DEA), the research endeavors to extract meaningful findings. The study's outcomes underscore the efficiency of American Airlines, Indigo, and Spirit Airlines throughout the research timeframe. Conversely, Ryanair, LATAM, China Southern Airlines, Air China, British Airways, Emirates, and China Eastern Airlines exhibited relative inefficiency during the analyzed interval. This research underscores the pivotal role of financial efficiency in the resilience and competitive standing of the airline sector, particularly during the formidable challenges posed by the COVID-19 pandemic.

Keywords Aviation · Efficiency · COVID-19 · Data Envelopment Analysis

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Financial Efficiency in Airlines During the COVID-19 Pandemic: A DEA Approach

The airline industry is a competitive sector in which most airline companies face challenges in retaining passengers and achieving sustainable profitability (Guo et al., 2023). The competition between national and international airline companies continues to increase over time. Companies compete by differentiating themselves on issues such as price, destination, and additional services offered to passengers. Therefore, to survive in this competitive environment, an airline must be able to offer and sell more air services while using fewer resources (Yu & Nguyen, 2023). It is crucial for airline companies to exhibit effective financial performance across a diverse stakeholder base (Kızıl & Aslan, 2019). The presence of resources is another factor that can influence competition in the airline industry. In the globalized world, businesses operating in the middle of intense competition need to survive and gain an edge over competitors in a challenging environment. Enhancing performance by efficiently using resources holds significant importance (Ağ & Kuloğlu, 2020). Airlines with greater resources are generally better equipped to compete in factors such as service quality and innovation. Financially efficient airlines possess a competitive advantage over those that are not. This is because financial efficiency allows airlines to operate at lower costs, enabling them to offer lower fares while still generating profits. Financial efficiency can be achieved through various methods, including reducing operating costs, improving revenue management, and enhancing productivity. Therefore, effective management plays a critical role in the financial performance of businesses (R. Mahesh & Prasad, 2012).

The transport industry, encompassing both passenger transportation (such as airlines, trains, buses, etc.) and freight transportation (shipping, trucking, etc.), has experienced significant negative effects due to the COVID-19 pandemic (Tardivo et al., 2021). Therefore, it is important to comprehend the various and interconnected impacts that the COVID-19 pandemic has had on the transportation sector (Habib & Anik, 2023). In the middle of the unforeseen crisis caused by the COVID-19 pandemic, comprehending the essential factors that impact airline performance has become increasingly crucial (Kaya et al., 2023). The year 2020 is described as the most difficult year for the aviation industry so far, and there are deep differences from the previous crises (Taşdemir & Aydın, 2021). With the declaration of a pandemic by the World Health Organization in March 2020, quarantines and closures were experienced around the world. In pandemic conditions, where physical social distance is essential, the aviation sector has been heavily affected by this crisis, as passengers generally travel by vehicles requiring physical proximity. The historical dissemination of diseases such as SARS and other severe acute respiratory infections has underscored the pivotal role of civil aviation air travel as a principal conduit for the inter-regional transmission of viruses (Xie et al., 2022). With the introduction of travel bans worldwide, flights were canceled, and airlines had to stop their operations to minimize their losses during this period. According to the October 2020 report of The International Air Transport Association (IATA), revenue passenger kilometers (RPK) across the industry shrank by 94.3% year-on-year in April, which was the largest contraction in recent history among large-scale quarantines linked to COVID-19 (IATA, 2020). Afterward, according to a report by Statista, during the week of June 1, 2020, there was a 65.1% decline in the number of flights that were scheduled globally when compared to the same week in the previous year, which was June 3, 2019 (Statista, 2023). Because of the canceled flights, airlines around the world had to reduce their employee numbers. According to a BBC news report on the airline industry dated June 11, 2020, Lufthansa intends to eliminate 22,000 positions. After losses of $42 billion and $137.7 billion in 2021 and 2020, respectively, the loss in 2022 is expected to be announced as a net $6.9 billion (IATA, 2022). Occurrences like the COVID-19 pandemic have severely and unexpectedly disrupted airlines that were otherwise efficiently managed, compelling them to declare bankruptcy due to a significant reduction in their available funds (Ng et al., 2023). These challenges faced by airlines have not only affected their own industries but also had far-reaching implications for the global economy (Peoples et al., 2020). The pandemic has accelerated existing trends in the industry, such as the shift toward low-cost carriers and the adoption of digital technologies. These changes may lead to increased competition and changes in efficiency scores as airlines adapt to the new landscape (World Economic Forum, 2020).

During COVID-19, especially, overseeing and safeguarding the effectiveness of companies has become crucial to ensure their continued existence. However, there are limited studies in the literature to measure airline efficiencies during the COVID-19 pandemic period (Asker, 2023; Kiraci & Asker, 2021; Tanrıverdi et al., 2023; Wu et al., 2024). Therefore, this study aims to analyze the financial efficiency of airlines during this period comparatively. Many studies have been conducted to measure efficiency in the airline industry over time (Asker, 2018; Asker & Aydın, 2021; Kiracı & Asker, 2019), and literature reviews reveal that Data Envelopment Analysis (DEA) developed by Charnes et al. is the most essential tool for assessing efficiency changes in the industry. In this study, the financial efficiencies of the 19 airlines with the most scheduled RPK according to the IATA 2021 World Air Transport Statistics (WATS) report were determined using the DEA method.

The original contribution of this study lies in its focus on quantifying the financial efficiency of airlines during the COVID-19 pandemic and comparing their performance over time. Additionally, it highlights how variations in efficiency relate to airlines' operational strategies and resource use. By adding to the existing literature on airline efficiency during global crises, this research provides a robust framework for understanding the financial resilience of airlines under adverse conditions.

Organization

The rest of the manuscript is organized as follows. Section 2 presents the relevant literature that has been used to address the efficiency analysis of aviation and the types of models used to study decision-making. Section 3 presents the theoretical framework and research methods used in this study. Then, the analysis results are presented and discussed in Section 4. Finally, the last section provides a summary of the findings as well as the conclusion and limitations of the study.

Literature Review

While there is a limited amount of research exploring the financial efficiency implications of the COVID-19 pandemic, various authors have tried to evaluate other aspects of airlines in the periods during and after the pandemic. In their study, (Mutascu & Sokic, 2023) used wavelet methodologies to analyze the co-movement between the COVID-19 pandemic and air transportation. The study's main findings revealed that the connection between the pandemic and air travel status was context-dependent, exhibiting significant variations across time and different time intervals, with notable correlations occurring mainly in the short term, coinciding with the virus's incubation period. (Pereira & Soares de Mello, 2021) evaluated the operational efficiency of Brazilian airlines considering the COVID-19 pandemic. They analyzed the first quarter of 2020 and the first quarter of 2019 through a Multicriteria DEA (MCDEA) model and mentioned the difficulties faced by airlines due to flight restrictions and a decrease in demand. The results of the analysis reveal that companies with better aircraft models have the advantage of operational efficiency in unpredictable periods such as the COVID-19 pandemic. (Macilree & Duval, 2020) in their work on selected aero-politic issues that may affect the international aviation industry after COVID-19, also examined the role of The International Civil Aviation Organization (ICAO) in this regard. (Maneenop & Kotcharin, 2020) approached the issue from a different perspective and analyzed the immediate effect of the COVID-19 pandemic in 2019 on 52 publicly traded global airline companies. The findings indicate that after the announcement of COVID-19, the decline in the stock returns of these airlines was more severe than that of the overall market.

Dube et al., 2021 examined the impact of the COVID-19 pandemic on the global aviation industry. The first study analyzed data from sources such as Flightradar24, ICAO, IATA, and EUROCONTROL and found that the pandemic caused significant damage to the industry, resulting in the closure and bankruptcy of several airlines and airports due to financial losses from travel restrictions. In another study, (Dube, 2022) also examined the effects of COVID-19 on aviation and identified challenges and opportunities for recovery. This study found that major aviation markets in Europe and the USA were experiencing difficulties such as labor shortages due to traffic disruptions and extreme weather events. Other challenges that the aviation industry is facing, such as mounting debt, rising inflation and interest rates, fuel costs, labor expenses, and overall operational costs. (Florido-Benítez, 2021) study aimed to analyze the effects of COVID-19 on airlines, airports, and Andalusia destinations. The study evaluated a range of factors related to how airlines responded to the COVID-19 pandemic, including bankruptcies, closures, and reductions in flight schedules. It also examined the measures taken by governments at airports to adjust to the new conditions and to efficiently allocate resources based on changes in tourist demand. As a result of the study, it was found that the sharp decrease in flight frequencies at airports during the pandemic caused an average of 65% decrease in the number of passengers arriving at the airports until October 2020, that is, 23 million passengers. The effects of some global crises on the aviation sector were analyzed in the study of (Tunalı, 2022) based on secondary data and sectoral reports. A case study and SWOT analysis were used to understand the strategies implemented by Qatar Airways, which are considered beneficial against the COVID-19 pandemic.

Some studies address the resilience strategies of airlines during past crises, which can provide a comparative perspective on how airlines have historically adapted to external shocks. (Taşdemir & Aydın, 2021), in their studies, deeply touched upon the various crises that have impacted the aviation sector in the past, including the OPEC oil embargo, the September 11 attacks, and epidemics such as SARS, MERS, and bird flu. It analyzed how airlines have responded to these crises and developed exit strategies. The study also examined the losses suffered by the aviation industry due to the COVID-19 pandemic and compared the severity of this crisis to previous ones. (Button & Taylor 2000)'s paper examines the recovery strategies that airlines implemented following the 9/11 attacks, such as capacity reduction, cost-cutting measures, and alliances to maintain operational continuity. This study highlights the role of government bailouts and regulatory relaxation in supporting airline recovery. (Lohmann & Koo 2013) investigated how airlines dealt with the significant downturn in passenger traffic during the SARS epidemic. Strategies included dynamic pricing, adjusting route networks, and focusing on regional markets with less travel restriction impact.

(Salman et al., 2020) when they aimed to analyze the adaptation of the airline industry after the impact of the coronavirus pandemic, they a qualitative analysis of the issue, analyzing how the airline industry faced such a challenge, how the airlines closed due to the huge debt they faced and how tourism fell sharply in all countries. In addition, the study proposes a set of policies to overcome the current crisis and similar periods in the future. The purpose of (Şenvar & Güneş Çağin, 2022) study is to investigate how the COVID-19 pandemic has affected the aviation industry, including airlines and airports, and its relationship with the tourism sector. The study used a descriptive approach and relied on secondary data and reports from various national, regional, and international authorities and institutions. By analyzing and interpreting global, European, and Turkish civil aviation data alongside tourism data from Turkey, the study compared the years 2019, 2020, and in some cases, 2021. The findings reveal that, unlike cargo traffic, passenger and air traffic in the world, Europe and Turkey were greatly affected by the pandemic that caused critical losses in airlines and airports in 2020.

In addition, studies are conducted with the Data Envelopment Analyze (DEA) on airline efficiency, apart from the effect of the pandemic. Table 1 summarizes the DEA-based airline efficiency models presented in the literature.

Table 1

Literature synthesis: DEA-based airline studies.

Authors	Scope	Period	Methodology	Inputs	Outputs
(Suau-Sanchez et al., 2025)	45 International airlines	2019-2022	NDEA	• Board • Executive Team • average length of the haul • market concentration	• ASK • Environmental • Social • network size • region and period
(Yang et al., 2024)	16 Iranian Airlines	2022	NDEA	• Fleet Size • Number of employees	• Seat-Kilometer Performed • Ton-Kilometer performed • Annual growth of Passenger share • CO2 emission
Khezrimotlagh and Kaffash 2024)	US airlines	2001-2021	Two-stage DEA	• Operational cost	• RPM • RTM
(Kaya et al., 2023)	35 International airlines	2019	Two-stage super-efficiency DEA	• Fleet size (FS) • Available Seat Kilometer (ASK) - Employee	• Service Quality • Claim processing • Operating income • Net Profit • On-Time Performance • Process Quality Index • Airline Safety Index • Operating Expenses - Atmospheric Emission Index
(Seth et al., 2023)	16 Indian Airlines	2014-2019	Hierarchical Categorical (DEA)	• Operating cost - FS	• Passenger revenue • Load factor
(Pereira & Soares de Mello, 2021)	3 Brazilian Airlines	2019-2020	MCDEA	• Number of Takeoffs • ATK • Fuel Consumed	• RTK
(Asker, 2021a)	36 International airlines	2013-2018	Two-stage DEA	• ASK • Number of employees • Fleet size	• Number of passengers • RPK • Factor Load • Net Profit/Net Sales • Net Profit/Total Assets
(Asker, 2021b)	31 International airlines	2016-2019	DEA	• Current Assets • Non-Current Assets • Current Liabilities • Non-Current Liabilities	• Net Profit • Net Sales • Market Values
(Peoples et al., 2020)	17 Asia-Pacific Region Airlines	2003-2011	DEA-MPI	• Fleet Size, • Fuel Consumption • Number of Employees	• RPK • Operating Revenue
(Min & Joo, 2016)	59 International Airlines	2010	DEA	• Operating Expenses • Underutilization	• Operating Revenue • Passengers • RPK • Service Rating
(Mallikarjun, 2015)	27 US Airlines	2012	DEA	• Operating Expenses • ASK • Fleet Size	• ASK • RPK - Operating Revenue

Authors	Scope	Period	Methodology	Inputs	Outputs
				• Destinations • RPM	
(Li et al., 2015)	22 International Airlines	2008-2012	Virtual Frontier Network SBM	• Number of Employees • Aviation Kerosene • ATK • ASK • Fleet Size • RTK • RPK • Sales Costs	• ATK • ASK • RTK • RPK • Total Business Income
(Lozano & Gutiérrez, 2014)	16 European Airlines	2007	slacks-based network DEA	• fuel cost • non-current assets • wages and salaries • other operating costs • ASK • ATK • selling cost	• ASK • ATK • RPK • RTK
(Tavassoli et al., 2014)	11 Iranian airlines	2010	SBM-NDEA	• Number of passenger planes • number of employees • number of cargo planes • passenger-plane-km • cargo-plane-km	• passenger-plane- km • cargo-plane-km • passenger-km • ton-km
(Gramani, 2012)	34 Brazilian and American airlines	1997-2006	two-phase DEA	• Aircraft fuel • Wages • salaries and benefits • cost per ASM	• RPK • flight revenue • flight income
(Lu et al., 2012)	30 US airlines	2006	two-stage DEA	• number of employees • fuel consumption • total number of seats • cost of the flight equipment • maintenance expenses • cost of equipment and property • ASM • ATM	• ASM • ATM • RPM • Non-Passenger Revenue
(Zhu, 2011)	21 International Airlines	2007-2008	DEA	• CASM • Salaries • ASM • wages per ASM • benefits per ASM • fuel expense per ASM • load factor • fleet size	• load factor • fleet size • RPM
(Chiou & Chen, 2006)	Taiwanese domestic airline	2001	DEA + Tobit regression	• Fuel Cost • Personnel Cost • Aircraft Cost • Number of Flights • Seat-Miles	• Number Of Flights • Seat-Miles • Passenger-Miles • Embarkation Passengers

This study aims to compare the financial efficiency of airlines during the COVID-19 period as reported in the existing literature. In this direction, the financial data of the 19 airlines selected for both the years before the COVID-19 pandemic (2017-18-19) and the years during the pandemic period (2020-21) were compiled from the annual reports of the airlines. The financial efficiency of the airlines will be determined by analyzing the collected data with DEA.

The Research Methodology

Data envelopment analysis framework

DEA is a method that identifies the most efficient observations within a given set, in other words, the DMUs that constitute the efficiency boundary, based on the output they produce relative to the input they use. In other words, it determines the observations that generate the highest level of output while using the least amount of input. It accepts the mentioned limit as a "reference" and measures the efficiency levels of inefficient DMUs radially to this limit. DEA provides a single efficiency score for each observation by using multiple input and output variables in a linear programming model (Depren, 2008). If the efficiency value is equal to 1, the DMU is efficient. On the other hand, if the efficiency value is less than 1, the DMU is not efficient (Aydın, 2022).

DEA was employed in this study due to its exceptional suitability for evaluating the relative efficiency of multiple Decision-Making Units (DMUs), such as airline carriers, especially in the context of optimizing resource utilization during the unprecedented challenges posed by the COVID-19 pandemic. Among the various efficiency evaluation methods, DEA is particularly advantageous for several reasons. First, it allows the simultaneous consideration of multiple input and output variables, which is essential for capturing the complex, multidimensional aspects of airline efficiency. Unlike parametric methods that require predefined functional forms, DEA operates without explicit assumptions about the relationship between inputs and outputs, making it a robust and versatile tool for application in diverse settings. Furthermore, DEA enables comparative efficiency analysis, identifying best practices and areas for improvement across the airlines under study. These capabilities are critical in an industry as dynamic and multifaceted as aviation, where external factors such as global pandemics can significantly impact operations.

A key factor for selecting DEA in this study is its ability to handle datasets with diverse variables and provide meaningful efficiency scores for both pre-pandemic and pandemic periods, where external shocks have introduced additional complexity into operational performance metrics. DEA's data-driven approach offers unique insights into how airlines adapted to these conditions, contributing to strategic decision-making in uncertain environments.

In the study, efficiency performance analysis was carried out within the framework of the input-oriented BCC (Banker, Charnes, Cooper) model under the assumption of variable returns to scale (VRS) using DEA and the input and output variables of 19 airline companies. In line with the determined inputs and outputs, the DEA models were analyzed with the DEA Solver 3.0 package program, which is an add-on to the MS Excel program. In the study, calculations of the technical efficiency-variable return to scale (VRS) efficiency score were made using the DEA method. technical efficiency refers to a company's capacity to achieve the highest possible level of output using a specific set of inputs or to achieve a certain level of output by utilizing the lowest possible number of inputs (Cooper et al., 2007). In this respect, in this study, the 5-year (2017-2021) data of 19 airlines were analyzed by the DEA method; pre-pandemic and pandemic financial efficiency scores of airlines were obtained.

DEA input and output variables

The 19 airlines considered in the study were selected among the 25 with the most scheduled RPKs in the IATA 2021 WATS report. Since it was not possible to reach the data of 5 of the 25 airlines identified in the report, these 5 airlines were excluded from the analysis. In particular, the data of low-cost airline companies that do not offer public offerings or are not members of any partnership (such as Star Alliance, One World, and Sky Team) are not regularly published on an annual basis, so it is not possible to analyze such airlines within the scope of the study. Since 2 of the remaining 20 airlines (KLM and Air France) are joint group companies, their data are published jointly and therefore they are considered as a single airline in the study. As a result, the data used in the analysis were obtained from the annual reports of 19 airlines between the years 2017 and 2021.

The rationale for the selection of input variables—Operating Expenses (OS), Total Assets (TA), and Total Liabilities (TL)—was grounded in their relevance to resource allocation and utilization within the airline industry. Operating Expenses represent the direct costs incurred by airlines in their operations, making them a critical measure of operational efficiency. Total Assets, which reflect the scale of resources available to an airline, were included to evaluate how effectively these resources are used to generate outputs. Total Liabilities were selected to capture the financial obligations of the airlines, providing insight into their leverage and financial management efficiency.

The choice of these variables was supported by a thorough literature review, which indicated their frequent use in studies examining financial and operational efficiency in the aviation sector. By incorporating both the operational and financial dimensions, the selected input variables offer a comprehensive framework for assessing efficiency. This approach aligns with the established methodologies in DEA and ensures that the model captures the nuanced interplay of factors impacting airline performance.

Output variables—Net Sales (NS) and Net Profit (NP)—were chosen to reflect critical financial performance indicators. However, a notable challenge arose from the negative profits reported by most airlines during the 2020 and 2021 pandemic years. To address this, and in line with DEA modeling requirements, a fixed value was added to the net profit variable for those years (15,000,000 USD for 2020 and 5,000,000 USD for 2021) to ensure that all data points remained non-negative, allowing for continuity in the analysis.

This rigorous approach underscores the suitability of DEA in capturing both the operational and financial efficiency of airlines under varying market conditions, thereby reinforcing the method's appropriateness for the study.

DEA is a mathematical model used to measure the efficiency of a DMU set with multiple inputs and outputs. In this study, an input-oriented model was used, aiming to minimize the input quantity as much as possible while maintaining the current output level. Accordingly, assuming that the 19 homogeneous DMU ($KVBj$, j = 1,....19) produce two outputs yrj (r =1,2) based on three inputs xij (i =1,2,3) and considering that the vectors xj = ($x1j$, ..., $x3j$) and yj = ($x1j$, ..., $y7j$) are positive and non-zero vectors, the mathematical model of the study has been formulated as an equation that mathematically represents the relationship between inputs and outputs.

Accordingly, the model is expressed as;

Model Assumptions:

- Model dealing with 19 DMUs (j=1,...,19).
- There are three inputs (x_1=OE, x_2=TA, x_3=TL) and two outputs (y_1=NS, y_2=N).
- The model is input-oriented, aiming to minimize the input usage while maintaining the current output level.

Model Formulation:

The standard input-oriented DEA model, based on the Variable Returns to Scale (VRS) assumption, can be described as

$$\min \theta_0 \tag{1}$$

subject to:

$$\sum_{j=1}^{19} \lambda_j x_{ij} \leq \theta_0 x_{i0}, \quad \forall i \tag{2}$$

$$\sum_{j=1}^{19} \lambda_j y_{rj} \geq y_{r0}, \quad \forall r \tag{3}$$

$$\sum_{j=1}^{19} \lambda_j = 1 \tag{4}$$

$$\lambda_j \geq 0, \quad \forall j \tag{5}$$

where:

- θ_0 is the efficiency score for the 0^{th} DMU.
- X_{ij} represents the i^{th} input for the j^{th} DMU.
- y_{rj} represents the r^{th} output for the j^{th} DMU.
- λ_j are the intensity variables.

Equation **(1)** minimizes θ_0, which scales down the inputs for the DMU under evaluation.

Equation **(2)** ensures that the weighted sum of the outputs for the reference DMUs (those used in comparison) is at least as great as the output for the DMU being evaluated (y_{r0}). This maintains the output level while reducing the inputs.

Equation **(3)** guarantees that the weighted sum of the inputs for the reference DMUs should be less than or equal to the scaled input for the DMU being evaluated ($\theta_0 x_{i0}$).

Equation **(4)** $\sum_{j=1}^{19} \lambda j$ ≤ =1 ensures that the solution is a convex combination of the DMUs, aligning with the VRS assumption.

Equation **(5),** the non-negativity constraint on λ_j , ensures that the weights are non-negative.

Descriptive statistics of the financial input and output variables used in the study are shown with the help of Table 2 below.

Table 2

Descriptive statistics of the financial variables.

Year	Variables	Max	Min	Mean	Std. Dev.
	Financial Inputs				
	Operating Expenses(000$)	39.346.963	2.258.727	17.466.380	11.880.823
	Total Assets(000$)	53.671.000	3.253.911	26.302.013	14.876.194
2017	Total Liabilities(000$)	53.565.000	2.163.998	19.950.758	13.316.928
	Financial Outputs				
	Net Sales (000$)	42.622.000	2.643.552	19.180.888	12.891.567
	Net Profit (000$)	11.400.000	155.304	1.844.856	2.448.299
2018	*Financial Inputs*				

Year	Variables	Max	Min	Mean	Std. Dev.
	Operating Expenses(000$)	41.885.000	2.972.120	19.324.656	12.738.617
	Total Assets(000$)	60.580.000	3.656.082	28.578.327	16.460.823
	Total Liabilities(000$)	60.749.000	2.640.929	22.072.525	14.939.441
	Financial Outputs				
	Net Sales (000$)	44.541.000	3.323.034	20.762.059	13.569.693
	Net Profit (000$)	3.935.000	(886.543)	1.155.359	1.159.155
	Financial Inputs				
	Operating Expenses(000$)	42.703.000	3.329.489	19.496.772	12.775.954
	Total Assets(000$)	64.532.000	5.972.291	31.559.149	17.722.296
2019	Total Liabilities(000$)	60.113.000	4.782.080	24.749.404	15.467.244
	Financial Outputs				
	Net Sales (000$)	47.007.000	3.830.536	21.075.545	13.751.190
	Net Profit (000$)	4.767.000	(35.246,00)	1.274.099	1.207.792
	Financial Inputs				
	Operating Expenses(000$)	29.564.000	2.317.784	12.132.011	8.321.208
	Total Assets(000$)	71.996.000	5.807.348	32.163.403	19.074.867
2020	Total Liabilities(000$)	70.462.000	5.792.394	28.898.874	19.223.200
	Financial Outputs				
	Net Sales (000$)	17.337.000	1.810.022	8.421.160	5.277.996
	Net Profit (000$)*	14.571.300	2.615.000	10.953.457	3.459.892
	Financial Inputs				
	Operating Expenses(000$)	30.941.000	3.287.649	13.690.207	8.436.729
	Total Assets(000$)	72.459.000	6.216.714	34.321.865	20.483.952
2021	Total Liabilities(000$)	73.807.000	6.425.990	30.831.612	20.075.760
	Financial Outputs				
	Net Sales (000$)	29.899.000	3.230.775	12.791.591	8.292.359
	Net Profit (000$)**	5.977.000	352.858	3.790.655	1.538.472

* +15.000.000$ added.
** +5.000.000$ added.

Findings

Analytical Estimates of DEA

The table showing the financial efficiency and total average efficiency of the DMUs within the scope of the study in the selected period range is as follows.

Table 3
*DMUs' Financial Return to Scale Efficiency **

DMUs	2017	2018	2019	2020	2021	Average
American Airlines	1,000	1,000	1,000	1,000	1,000	1,000
IndiGo	1,000	1,000	1,000	1,000	1,000	1,000
Spirit Airlines	1,000	1,000	1,000	1,000	1,000	1,000
Delta Airlines	1,000	1,000	1,000	0,929	1,000	0,986

DMUs	2017	2018	2019	2020	2021	Average
Air France + KLM	0,961	0,967	1,000	1,000	1,000	0,986
Southwest Airlines	1,000	1,000	1,000	0,927	1,000	0,985
Lufthansa	1,000	1,000	1,000	1,000	0,894	0,979
United Airlines	1,000	1,000	1,000	1,000	0,889	0,978
JetBlue	1,000	0,933	1,000	0,878	1,000	0,962
Alaska Airlines	0,976	0,952	0,984	0,892	1,000	0,961
Aeroflot Russian airlines	0,888	0,952	0,954	0,976	0,962	0,947
Turkish Airlines	0,869	0,938	0,896	1,000	1,000	0,941
Ryanair	1,000	0,989	0,99	0,841	0,842	0,932
LATAM	0,85	0,919	0,924	0,914	0,815	0,884
China Southern Airlines	0,861	0,875	0,889	1,000	0,778	0,881
Air China	0,894	0,922	0,928	0,943	0,689	0,875
British Airways	0,962	1,000	1,000	0,797	0,607	0,873
Emirates	0,884	0,901	0,921	0,753	0,903	0,873
China Eastern Airlines	0,829	0,865	0,876	0,839	0,682	0,818

* The value of VRS=0.99 was accepted as VRS=1 when interpreting.

As indicated in Table 3, among the 19 DMUs, American Airlines, IndiGo and Spirit Airlines are the DMUs that have operated within the efficiency limit throughout all periods with an efficiency score of VRS=1. While Spirit Airlines had the lowest OE and NS values in all periods, IndiGo was determined as the DMU with the lowest TA input value during the 5-year period. The lowest value of the TL input varied between Spirit Airlines and IndiGo. In addition, American Airlines reached the highest NS output in 2017-18 and 2020 and operated with the highest TL input value in all years except 2020. From this point of view, it is possible to state that the important issue in efficiency analysis is not the high and low values of input and output, but the proportional relationship between them.

It is seen that Delta Airlines and Southwest Airlines companies moved away from the efficiency limit only in 2020, when the impact of the COVID-19 pandemic on airlines was intense, and they operated effectively in other years. Looking at their general averages, it is seen that they are in a very competitive position financially. Similarly, it is understood that the Air France + KLM group company, which is seen to have a high competitive advantage with a VRS=0.9856 efficiency score on a general average basis, was far from the efficiency limit in 2017-18. In 2019-20 and 2021, it managed to reach the efficiency limit.

Lufthansa and United Airlines companies moved away from the efficiency limit only in 2021 and continued their activities financially in other years. Based on general averages, it is possible to say that these two DMUs have a financial competitive advantage in the sector. It has been revealed that Aeroflot Russian Airlines, LATAM, Air China, Emirates, and China Eastern Airlines have never reached the efficiency limit within the scope of the analysis.

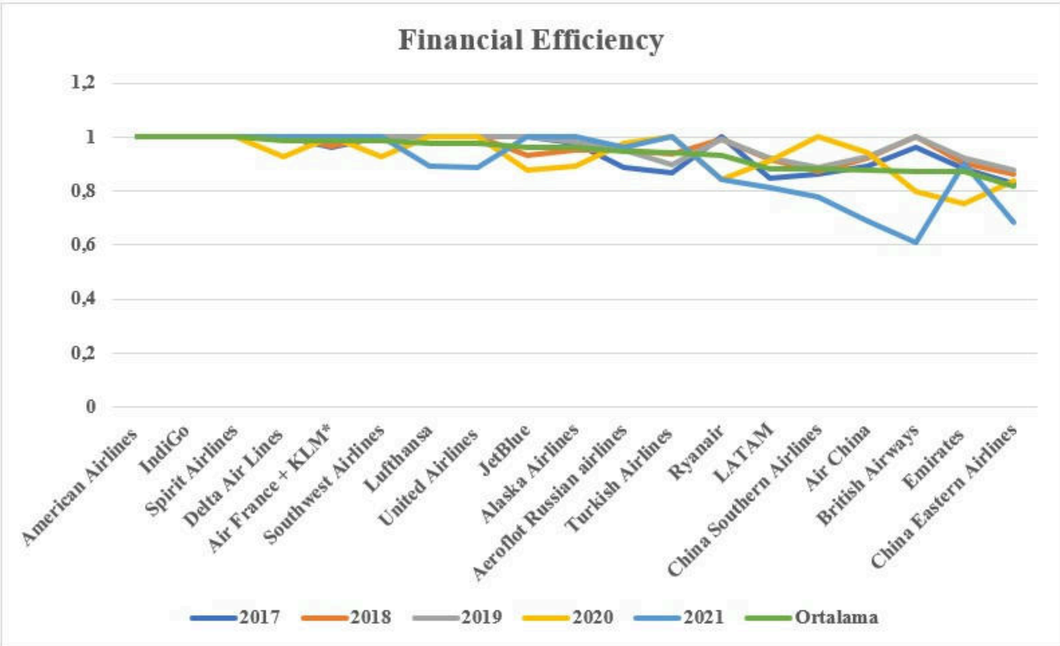
China Eastern Airlines has been identified as the DMU with the lowest average among the DMUs on an average basis. Along with it, other Chinese-origin DMUs (China Southern Airlines and Air China) ranked 15th and 16th in the average ranking. It is noteworthy that all three DMUs reached their lowest scores, especially in 2021. From this point of view, it should be noted that DMUs of Chinese origin do not have a financial competitive advantage in the sector and they need improvements at this point. On the other hand, it can be said that both low-cost and full-service DMUs of American origin are more successful in terms of financial efficiency. Although Alaska Airlines was found to be the most inefficient American origin DMU in general averages with a VRS = 0.9607 efficiency score among American airlines, it can still be considered as having an efficiency that maintains its advantage in terms of competition.

During the pandemic, many airlines adopted operational adjustments to mitigate its financial impact. These included aggressive cost-cutting measures, restructuring of debt, optimizing fleet utilization, and renegotiating contracts. For instance, several airlines reduced operating expenses by grounding less efficient aircraft, implementing temporary layoffs, and delaying capital expenditures. Spirit Airlines and IndiGo, which maintained efficiency throughout the period, demonstrated strong cost management by aligning their input resources proportionately to the reduced demand. American Airlines maximized its high NS output by leveraging its network and operational scale, despite maintaining higher liability levels.

A graphical representation of the distribution of the financial efficiencies of DMUs over the years is given below in Chart 1.

Chart 1

Return to the Financial Scale Efficiencies of Airline Companies



From a financial perspective, it is clear from Chart 1 that the biggest fluctuations in efficiencies were experienced in 2021, and DMUs generally moved away from the efficiency limit in 2020. It is seen that American Airlines, IndiGo, Spirit Airlines, Delta Airlines, Southwest Airlines and Air France + KLM group companies generally operate at the efficiency limit on average. In addition, although there are periods when Lufthansa, United Airlines, JetBlue Airways, Alaska Airlines, Aeroflot Russian Airlines, THY and Ryanair need improvement, it is possible to say that they are DMUs that have a financial advantage in the competitive environment in the sector.

On the other hand, LATAM, China Southern Airlines, Air China, British Airways, Emirates and China Eastern Airlines are DMUs operating far from the financial efficiency limit. Therefore, they need to make improvements in the input values, and the identified Idle Usages and potential improvement rates are presented in detail in Table 4. It is possible to say that DMUs will not be able to gain a financial competitive advantage in the current situation; therefore, they should move themselves among the effective DMUs by taking the effective DMUs in the sector as a reference.

Table 4
Financial Potential Improvement (PI) for All DMU's in 2021 (Input Oriented, BCC)

DMU	Score	Reference	OE (000$)		TA (000$)		TL (000$)	
			IU	PI%	IU	PI%	IU	PI%
American Airlines	1,000	-	0	0	0	0	0	0
Delta Airlines	1,000	-	0	0	0	0	0	0
Southwest Airlines	1,000	-	0	0	0	0	0	0
Turkish Airlines	1,000	-	0	0	0	0	0	0
Air France + KLM	1,000	-	0	0	0	0	0	0
IndiGo	1,000	-	0	0	0	0	0	0
JetBlue Airways	1,000	-	0	0	0	0	0	0
Spirit Airlines	1,000	-	0	0	0	0	0	0
Alaska Airlines	1,000	-	0	0	0	0	0	0
Aeroflot Russian Airlines	0,9616	Alaska Airlines	258.600	−4	577.565	−4	5.561.420	−33
Emirates	0,9027	Southwest Airlines	1.580.174	−10	3.975.323	−10	7.414.079	−21
Lufthansa	0,8941	Southwest Airlines	5.472.282	−22	5.328.979	−11	4.766.491	−11
United Airlines	0,8891	Delta Airlines	2.846.443	−11	9.201.890	−13	10.495.722	−17
Ryanair	0,8419	Alaska Airlines	961.683	−16	4.883.476	−27	1.839.978	−16
LATAM	0,8154	Alaska Airlines	1.150.341	−18	2.457.834	−18	11.466.475	−56
China Southern Airlines	0,7784	Southwest Airlines	3.995.809	−22	13.845.075	−28	11.135.674	−30
Air China	0,6894	Turkish Airlines	4.595.318	−31	18.051.352	−39	15.291.722	−42
China Eastern Airlines	0,6819	Turkish Airlines	4.275.330	−32	19.009.182	−42	16.798.565	−47
British Airways	0,6071	Alaska Airlines	3.022.883	−39	13.176.534	−52	13.634.396	−61

The potential improvement rates obtained due to the input-oriented approach of the performance analysis explain how much improvement each airline needs in which input, based on the results presented in Table 4. According to the analysis results presented in Table 4, British Airways, which completed the year 2021 with the lowest efficiency score, had the highest idle usage (IU) in its input values with a total liabilities input of 13,634,396 USD, and it is recommended that it should achieve a potential improvement of 61% for the DMU. For the idle (IU) usage determined at 13,176,534 USD in the total assets input, it is estimated that it can achieve a potential improvement of 52%. In the case of the airline with the highest idle usage among the DMUs, idle usage was also determined in the total operating expenses input, with 3,022,883 USD, and it was revealed that the idle usage in the input could be compensated with a potential improvement of 39%. Alaska Airlines, on the other hand, has become the reference airline with the highest density recommended for the DMU.

When examining Chinese-origin DMUs, it is evident that the most substantial underutilized input is found within the total liability category. Specifically, a potential enhancement of 47% is recommended for China Eastern Airlines, 42% for Air China, and 30% for China Southern Airlines within the total liabilities input. In precise terms, the DMUs exhibited underutilized input amounts of 16,798,565 USD, 15,291,722 USD, and 11,135,674 USD liabilities, respectively. Furthermore, in the total assets input, China Eastern Airlines showcases an underutilized input of USD 19,009,182, while Air China and China Southern Airlines display underutilized inputs of USD 18,051,352 and USD 13,845,075, respectively. Correspondingly, the recommended potential improvement rates for these DMUs were 42%, 39%, and 28%, respectively. In the context of total operating expenses, China Eastern Airlines recorded an underutilized input of 4,275,330 USD, Air China recorded 4,595,318 USD, and China Southern Airlines reported 3,995,809 USD. The suggested Potential

Improvements (PI) for DMUs in the total operating expenses input are 32%, 31%, and 22%, respectively. Additionally, Turkish Airlines (THY) serves as a reference for China Eastern Airlines and Air China for improvement recommendations aimed at reaching the efficiency frontier. As for China Southern Airlines, Southwest Airlines is recommended as the reference DMU with the highest density.

The COVID-19 pandemic forced airlines to make drastic operational adjustments to survive the unprecedented crisis. Efficient airlines, such as American Airlines, IndiGo, and Spirit Airlines, successfully implemented strategies to mitigate financial and operational risks. IndiGo and Spirit Airlines optimized their cost structures by renegotiating supplier contracts and reducing discretionary expenses. Spirit Airlines, with its ultra-low-cost model, leveraged its lean operational framework to align input costs with reduced demand. Airlines such as Delta and Southwest optimized their route networks by suspending less profitable routes and reallocating resources to cargo operations or routes with sustained demand. Delta also capitalized on its strong domestic network, which rebounded faster than international travel. Additionally, many airlines, including Lufthansa and Emirates, increased their reliance on cargo services during the pandemic. Lufthansa, for instance, converted passenger aircraft into freighters, taking advantage of the surge in global air freight demand.

Discussion and Conclusion

In this study, the financial performances of 19 IATA member airline companies between the years 2017 and 2021 were comparatively evaluated. First, the efficiency values for the financial statements were calculated using DEA with the model in question. In general, most scheduled RPKs according to the IATA 2021 WATS were observed

Our DEA findings reveal that American Airlines, Indigo, and Spirit Airlines were identified as efficient for all years, including the COVID-19 pandemic period. In other words, by making a comparative evaluation in line with the existing resources and outputs, it has been understood that the companies produce effective outputs by using the available resources in an optimum way. On the other side, Ryanair, LATAM, China Southern Airlines, Air China, British Airways, Emirates, and China Eastern Airlines are DMUs that are far from the efficiency limit according to the averages of the periods discussed. In terms of resource utilization, the category of Total Liabilities emerges as the input where the most significant level of inefficiency has been observed.

According to the DEA calculations, it is evident that British Airways is the airline that needs to achieve the highest potential improvements in its inputs at the end of the analysis period, which is the latest year 2021. To reach the efficient production frontier, British Airways should reduce its operating expenses, total assets, and total liabilities inputs by 39%, 52%, and 61%, respectively.

The findings reveal that financial efficiency among airlines during the COVID-19 pandemic varied significantly, with some airlines demonstrating resilience through strategic cost management and resource allocation, while others experienced inefficiencies. This is consistent with the findings of Pereira & Soares de Mello (2021), who observed that airlines with more advanced aircraft models and operational strategies were better able to maintain efficiency during unpredictable periods like the pandemic. Similarly, our study corroborates the observations of Salman et al. (2020), who emphasized the importance of adaptive management strategies to mitigate the financial impacts of the pandemic on airlines. However, unlike the qualitative approaches employed by studies such as Dube (2022) and Florido-Benítez (2021), which highlighted broader challenges like labor shortages and changes in passenger demand, our analysis provides quantitative evidence of efficiency variations through DEA. This allows for a more detailed examination of how specific input-output dynamics contributed to the observed financial performance of airlines. Our study also aligns with the conclusions drawn by Şenvar & Güneş Çağin (2022), who noted a disproportionate impact on passenger and air traffic compared to cargo operations during the pandemic. The DEA results highlight that airlines with a stronger focus on cargo services managed to maintain higher efficiency scores, a trend similarly identified in Şenvar & Güneş Çağin's comparative analysis of Turkish and global aviation data. Moreover, the findings extend the work of Tunalı (2022), who emphasized the strategic adjustments made by airlines like Qatar Airways to counteract pandemic-induced challenges. In our study, airlines that implemented cost-cutting measures, diversified revenue streams, and leveraged technological advancements showed higher efficiency, confirming the broader effectiveness of such strategies in enhancing resilience. While Maneenop & Kotcharin (2020) highlighted the short-term financial losses of publicly traded airlines immediately after the pandemic's onset, our study demonstrates that long-term financial efficiency varied significantly depending on the airlines' adaptability. This underscores the necessity of proactive and sustained strategic interventions for financial stability.

Management should allocate all financial resources in line with company objectives and use these resources in the most efficient and profitable manner. To achieve this, traditional financial planning methods should be employed, and budget processes should be regularly reviewed. Reducing operational costs should be a key goal for management. Fluctuations in fuel prices, on the other hand, pose a significant risk of airlines. Therefore, fuel price hedging strategies should be implemented. Policymakers should enact appropriate regulations to support the sector's sustainability and implement selective credit policies that support low-cost airline companies. This could enable low-cost airlines operating in competitive markets to gain a better competitive advantage.

While this study provides valuable insights into the efficiency performance of airlines during pre-pandemic and pandemic periods using DEA, certain limitations must be acknowledged.

The models in this study were formed according to the available data. Even though the financial performances of IATA member airlines with the readily available data already assessed, the study can be replicated with updated data and new variables, as the outcomes generated using DEA may vary based on the specific variables and data included or excluded in the model. One notable limitation is the relatively small sample size of 19 airlines. This sample was derived from the 25 airlines with the highest scheduled RPKs in the IATA 2021 WATS report. However, data availability constraints necessitated the exclusion of five airlines whose data were inaccessible and the combination of two airlines (KLM and Air France) due to their joint reporting practices. Additionally, low-cost airlines that do not provide public financial disclosures were excluded, further narrowing the sample. The small sample size poses potential challenges for the generalizability of the findings. While DEA is well-suited for benchmarking and efficiency analysis in small datasets, the limited number of DMUs restricts the study's ability to capture a broader representation of the global airline industry. As a result, the conclusions drawn from this analysis may not fully reflect the efficiency dynamics of airlines operating under different market structures, regulatory environments, or geographic regions.

Future research could address this limitation by expanding the sample size to include a more diverse range of airlines, potentially incorporating regional carriers or using alternative data sources to cover low-cost airlines. Additionally, integrating other efficiency evaluation methods alongside DEA could provide a more comprehensive understanding of airline performance and enhance the robustness of the findings. The study also acknowledges the impact of external factors such as the COVID-19 pandemic on airline efficiency. However, it may not fully account for other external factors such as regulatory changes, geopolitical events, economic fluctuations, or natural disasters, which could also affect airline performance.

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