EXAMINATION OF THE AVIATION PERFORMANCE OF G20 COUNTRIES

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ABSTRACT

In this study, the performance of G20 countries in the aviation sector in 2023 is analyzed comparatively. The aim is to reveal the extent to which countries are able to maximize their sectoral outputs with the available resources. Inputs (number of commercial airports, aviation investment, total number of employees) and outputs (annual passenger traffic, cargo volume, economic contribution of aviation) are considered. Turkey, USA, Germany, UK, China, France, South Korea, Indonesia, Argentina, Italy and South Africa were found to be fully efficient. In contrast, Australia, Brazil, India, Japan, Japan, Canada, Mexico, Mexico and Saudi Arabia were below the efficiency threshold. In particular, South Korea and the USA stand out as the most exemplary reference units for many countries. The findings provide policy recommendations for more efficient use of resources in the aviation sector.

Keywords: Data Envelopment Analysis, Aviation, G20 Countries, Efficiency.
Research Field: Aviation Economics, Operational Efficiency, Transportation Systems
Research Type: Research
JEL Codes: L93, C61, R41

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G20 ÜLKELERİNİN HAVACILIK PERFORMANSININ İNCELENMESİ

ÖZ

Bu çalışmada, G20 ülkelerinin havacılık sektöründeki 2023 yılı performansı karşılaştırmalı olarak analiz edilmiştir. Amaç, ülkelerin mevcut kaynaklarla sektörel çıktılarını ne ölçüde maksimize edebildiklerini ortaya koymaktır. Girdiler (ticari havalimanı sayısı, havacılık yatırımı, toplam çalışan sayısı) ve çıktılar (yıllık yolcu trafiği, kargo hacmi, havacılığın ekonomik katkısı) dikkate alınmıştır. Türkiye, ABD, Almanya, İngiltere, Çin, Fransa, Güney Kore, Endonezya, Arjantin, İtalya ve Güney Afrika'nın tam verimli olduğu görülmüştür. Buna karşılık, Avustralya, Brezilya, Hindistan, Japonya, Kanada, Meksika, Meksika ve Suudi Arabistan verimlilik eşiğinin altında kalmıştır. Özellikle Güney Kore ve ABD, birçok ülke için en örnek referans birimleri olarak öne çıkmaktadır. Bulgular, havacılık sektöründe kaynakların daha verimli kullanılması için politika önerileri sunmaktadır.

Anahtar Kelimeler: Veri Zarflama Analizi, Havacılık, G20 Ülkeleri, Verimlilik.
Araştırma Alanı: Nicel Araştırma, Veri Zarflama Analizi (DEA) ile Etkinlik Analizi
Araştırma Türü: Araştırma
JEL Kodları: L93, C61, R41

1. INTRODUCTION

With the increasing integration of the global economy in the 21st century, the aviation sector has become one of the main elements of international trade, tourism, and labor mobility (Button & Pels, 2010). G20 countries account for approximately 85% of the world economy and host a large portion of global air passenger traffic (ICAO, 2022). In this context, evaluating the effectiveness of these countries' investments in the aviation sector is of high importance not only from an economic but also from a strategic perspective. Due to its multi-dimensional structure, the aviation sector is not limited to transportation infrastructure; it also generates broad-ranging effects such as job creation, logistics efficiency, foreign trade performance, and economic contributions to the country (IATA, 2023). The “Value of Air Transport” country reports prepared by the International Air Transport Association (IATA) enables these impacts to be tracked annually with concrete indicators.

In this study, 2023 aviation sector data for G20 countries were analyzed using the DEA method. The inputs included the total number of commercial airports in each country, aviation investment (in millions of US dollars), and the total number of employees in the sector; the outputs included origin-destination passenger traffic, annual cargo volume, and the aviation sector's contribution to the country's economy. The analysis was conducted using constant return (CRS) and variable return (VRS) models; additionally, detailed interpretations were made through scale efficiency and sampling matrices.

The primary objective of this study is to analyze the level of output that G20 countries can produce with their current resources in the aviation sector and to evaluate the relative performance of countries. The comparative analysis conducted using input (number of commercial airports, total number of employees, aviation investments) and output (annual number of passengers, amount of cargo transported, sectoral economic contribution) indicators revealed the efficiency levels of the countries. The findings indicate that Turkey, the US, Germany, the UK, China, France, South Korea, Indonesia, Argentina, Italy, and South Africa have achieved full efficiency levels. However, In contrast, Australia, Brazil, India, Japan, Canada, Mexico, and Saudi Arabia were found to exhibit relatively lower performance. The analysis results not only identify the current situation but also determine the countries that should be taken as examples. In particular, the United States and South Korea stand out as the most frequently referenced model units by other countries. This suggests that these efficient countries often serve as benchmark examples in the aviation sector. Other nations may look to their practices for guidance, although the DEA results alone do not pinpoint which strategies or policies lead to higher efficiency.

This study fills an important gap in the literature by providing a comprehensive efficiency analysis that covers all G20 countries. While previous research has mostly focused on individual airlines, airports, or pre-COVID-19 periods, this paper examines the post-pandemic context using the most recent data from 2023. In addition, it incorporates two indicators that are rarely used in the literature: aviation investments as an input and the direct contribution of aviation to the national economy as an output. These variables highlight the economic returns of sectoral investments, making the study distinctive and offering a new perspective to the existing literature.

In this article, the general framework of the DEA method and its applications in the aviation sectorwill first be summarized based on previous studies in the literature, followed by an explanation of the method and data set. The next section will present the results of a Data Envelopment Analysis (DEA) conducted using 2023 data from G20 countries in detail. This section will include findings on technical efficiency, scale efficiency, baseline analyses, and input/output differentials. The final section will summarize the results, offer policy recommendations for inefficient countries, and offer suggestions for future research.

2. LITERATURE REVIEW

Today, the aviation sector is experiencing rapid growth due to technological developments and globalization. For example, global airline passenger traffic, which was approximately 300 million in 1970, reached 4.5 billion in 2019, and the sector's revenue rose to $507 billion (Cui & Yu, 2021). In light of this growth and increasing operating costs, it has become important for airlines and airports to use their resources efficiently and analyze their performance on a regular basis. In a global competitive environment, airports must use their resources efficiently and continuously measure their performance. In this context, the non-parametric Data Envelopment Analysis (DEA) method, which considers multiple input-output relationships, is widely applied as a tool for efficiency assessments in the aviation sector (Cui & Yu, 2021). Efficiency analysis, in particular, is one of the methods frequently used in performance evaluation processes.This type of analysis examines the efficiency with which a system utilizes inputs used in the production of goods or services. Within this framework, numerous studies in the literature, both domestically and internationally, have been conducted using the Data Envelopment Analysis (DEA) method to determine the relative efficiency of universities and faculties. Recent studies have shown that DEA is a widely used and effective tool for analyzing the resource utilization efficiency of different academic units (Çınaroğlu, Doruk & Avcı, 2018). Literature studies on performance and efficiency analysis in the aviation sector in Turkey are presented in Table 1 below.

Table 1. DEA Studies Conducted in the Field of Aviation in Turkey

Author	Countr y & Period	Method	Inputs	Outputs	Key Findings
Kocak (2011)	Turkey 2008	CCR Model (DEA)	Operating expenses, number of personnel, flight traffic,	Passenger s per area, flight traffic per runway, total cargo	According to 2008 data, airports such as Istanbul Atatürk, Antalya, and Kayseri were

			passenger numbers		found fully efficient.
Avcı & Aktaş (2016)	Turkey, 2013–2014	DEA (BCC Model)	Domestic: passenger numbers, aircraft traffic, terminal size; International: passenger numbers, cargo, aircraft traffic	Domestic: personnel number, apron area; International: personnel number, apron, terminal size	Airport efficiencies were compared by summer and winter seasons; seasonal performance differences were revealed.
Örkcü, Balıkçı, Doğan & Genç (2016)	Turkey, 2009-2014	CCR DEA + Malmquist TFP	Airport resources	Air traffic volume	A general increase in airport efficiency was observed between 2009 and 2014.
Calipinar & Koç, 2017	Turkey, 2011–2014	Malmquist TFP Index + Färe-Primont TFP	Infrastructure capacity and resource usage data	Passenger, flight and other service outputs	Highest efficiency increase was at Isparta airport; lowest at Tekirdağ and Çanakkale during 2011–2014.
Asker (2018)	Global, 2012	Comparison of CCR and BCC DEA	ASK (available seat-km), total seat capacity, number of employees, fuel costs	RPK (revenue passenger-km), load factor (%), total passengers	Most airlines were found efficient with the BCC model; effects of scale differences were emphasized.
Asker & Aydın (2021)	Global, 2010–2017	DEA (CCR, BCC) + Tobit regression	TC/TA, LTL/TA, FA/TA, CA/CL	NP/NS, NP/TA, NS/TC, NS/TA	Low-cost airlines were more efficient; large carriers outperformed medium-scale; profitability improved efficiency, capital intensity reduced it.

Yılmaz, Kuşakcı & Hacıoğlu (2022)	Turkey, 2015–2018	Integrated fuzzy AHP + DEA	Airport infrastructure and resource criteria	Airport operational outputs	Efficiency of 46 airports was examined with a hybrid method; external factors significantly affected efficiency.
Tunç et.al. (2024)	G20 Countries, 2015–2019	CCR & BCC DEA + Malmquist TFP	Country-level aviation indicators	Country aviation outputs	The position of Turkey within G20 countries and China was analyzed; recommendations were made for areas needing improvement.
Güner, Antunes, Seçkin Codal & Wanke (2024)	Turkey, 2017–2021	Two-stage weight-restricted Network DEA (CRITIC-NDEA)	Runway area, Terminal area, Apron area, Special-purpose vehicles; Population, Socio-economic development, Tourist arrivals	Degree, Betweenness, Eigenvector centrality, Aircraft movements, WLU	Weight-restriction improves robustness; inefficiency mostly from weak networkability (low betweenness); COVID boosted domestic networkability (direct flights) but reduced traffic generation.

Both Turkish and international studies utilize similar multiple inputs such as airport infrastructure (terminal area, number of runways, number of gates, etc.), number of employees, and investments, and outputs such as passenger and cargo traffic, revenue, and economic contribution. Classic CCR and BCC models are widely preferred in these studies. Turkish research, however, applies these international methods to the local context; for example, in a study of tourism-focused airports, inputs were used: number of employees, number of flights, and terminal capacity, and outputs were used: number of tourists and tourism revenue. Furthermore, studies addressing seasonal demand differences and comparing productivity between summer and winter periods are also available. Generally, both literatures utilize similar approaches using the multiple input-output structure of DEA, while Turkish studies emphasize specific dynamics of the country's economy, such as tourism and seasonality.

Literature studies on performance and efficiency analysis in the aviation sector abroad are presented in Table 2 below.

Table 2. DEA Studies Conducted Abroad in the Field of Aviation

Author	Country & Period	Method	Inputs	Outputs	Key Findings
Pels,Nijkamp & Rietveld (2003)	Europe (34 airports, 1995–1997)	CCR DEA +Comparison with frontier model	Number of runways (fixed factor), other infrastructure and expenses	Passenger movements, number of flights (movements)	Most European airports are not technically efficient; passenger density is a critical factor.
Bazargan & Vasigh (2003)	United States (45 airports, 2000)	CCR DEA	Operating expenses, non-operating expenses, number of runways, number of gates	Number of passengers, flight movements, other flight activities, aviation revenues, non-aviation revenues, on-time departure rate	Large airports are not always the most efficient; medium-sized airports can also use resources efficiently.
Scheraga (2004)	Global airline industry (1980–2000)	CCR DEA	Total capacity (ton-km), operating expenses, non-flight assets	Passenger revenues, total cargo revenues	The cost structure and fleet characteristics of airlines have been key determinants of efficiency.
Barros & Dieke (2007)	Italy (31 airports, 2001–2003)	Multiple DEA models	Labor costs, capital investment, operating expenses	Number of aircraft, number of passengers, cargo, ground service revenues, aviation revenues, commercial revenues	Passenger and commercial revenue generation improves efficiency in Italian airports.
Merkert & Hensher (2011)	Global (58 airlines, 2007–2009)	DEA (CCR) + Panel Tobit regression	Number of employees, personnel expenses, ATK, ATK costs	RPK (Revenue Passenger-Km), RTK (Revenue Ton-Km; passenger + cargo)	Fleet planning and business model are significant factors in airline efficiency.
Saranga & Nagpal (2016)	India (13 airlines, 2005–2012)	DEA (CCR) + Second stage regression	Number of employees, ASK, operating expenses, personnel costs	RPK (Revenue Passenger-Km), operating revenue	Low-cost carriers in India have demonstrated higher operational efficiency.

Coto-Millán et.al. (2016)	Spain (37 airports, 2009–2011)	DEA (CCR)	Airport infrastructure and expense variables	Passenger, cargo, and flight traffic data	While cargo transport increases scale efficiency in some airports, it may limit technical efficiency.
Martí, Martín & Puertas (2017	G20 and worldwide (Country-level logistics, 2014)	DEA-LPI	Logistics infrastructure indicators	Trade logistics outcomes	Countries with strong logistics infrastructure gain competitive advantage in trade.
Mhlanga (2020)	South Africa, 2015–2018	Bootstrapped Meta-frontier DEA	ASK (capital), FTE staff (labour), Operating expenditure, Aircraft number	Revenue passenger-km	Large aircraft, private and low-cost airlines more efficient; state carriers inefficient.
Cui & Yu (2021)	Global, 1993–2020	Literature review of DEA applications (radial, nonradial, network, dynamic DEA)	Labor, fuel, fleet size, costs, ASK/ATK, RPK/RTK, revenue, etc	Efficiency and productivity scores	Airline efficiency has improved; results vary by region and airline type; newer DEA models (network, dynamic, environmental) are increasingly used.
Chen, Cheng & Zhu (2021)	China, 2013–2018	Two-stage undesirable SBM-NDEA (Network DEA)	Number of employees, fleet size, aviation fuel	Intermediate: ASK, ATK; Final: Operating revenue, RPK, RTK; Undesirable: CO_2 emissions	Low-cost airlines showed highest efficiency; major carriers had lowest efficiency; inefficiency mainly stemmed from production stage.
Nguyen, Yu & Lirn (2022)	U.S., 2015–2019	Two-stage DEA (bootstrap non-convex meta-frontier + truncated regression)	Labor (FTE employees), Available Tonne-Miles (ATM), Fuel consumption	Total operating revenue	ULCCs least efficient; NLCs outperformed LCCs; efficiency driven by service quality, size, and ticket price.

Wang, Zhu, Zhang & Boocock (2023)	China, 2016–2019	Two-stage Network DEA (relational, BCC-VRS) + panel data regression	Runway area, Passenger terminal area, Total cost of revenue, Processed passengers	Airport non-aeronautical revenue	HKG most efficient; ops efficiency high, financial uneven; efficiency drivers: ASQ, AEZDL, airside (+), distance to city (−).
Bourjade & Muller-Vibes (2023)	Global, 2007–2019	Stochastic Frontier Analysis (SFA) + 2SLS	Operating costs, fleet structure, financial data	Cost efficiency scores	Leasing has a nonlinear effect; optimal level around 46%; LCCs/private airlines benefit more, FSCs/state-owned less.

Current studies generally rely on older data sets or more limited analyses. In this regard, this study, which uses data from 2023, provides a timely contribution to the literature. In addition, this research compares and analyzes nearly all G20 countries using a single data set. Tunç, Gök, Vural, Sarıkaya, Karaaslan & Çayır Ervural (2024) examined the activity levels of the aviation sectors in G20 countries and Turkey; however, it is observed that the study most likely includes pre COVID-19 data and more limited variables. In contrast, this study considers comprehensive input variables such as the number of commercial airports, investment expenditures, and the number of employees, along with output variables such as passenger traffic, cargo volume, and economic contribution. This different variable selection and expanded scope constitute an important aspect of the study that contributes uniquely to the literature.

3. METHODOLOGY

Before explaining the DEA models, it is important to clarify the concepts of efficiency and performance measurement in order to provide a theoretical basis for the analysis. Efficiency refers to the level at which maximum output can be achieved with specific inputs and indicates how efficiently resources are used (Farrell, 1957). This concept specifically highlights organizations' ability to minimize inputs while maximizing output. Performance measurement, on the other hand, is a systematic process that evaluates the extent to which an organization has achieved its objectives; Moullin (2003) defines it as "the evaluation of how organizations are managed and the value they provide to customers and stakeholders," while Neely (1999) defines performance measurement as "the quantitative measurement of the effectiveness and efficiency of past activities." Therefore, performance measurement encompasses dimensions such as efficiency, quality, and sustainability, in addition to the concept of effectiveness, allowing organizations to assess both whether they are doing things right and whether they are doing the right things.

The intense competition and high resource utilization in the aviation industry make these concepts even more important. Airlines and airports must regularly monitor indicators such as cost per seat, fuel efficiency, on-time departure rate, passenger numbers, and occupancy rate to assess their operational and financial performance. Efficiency analysis is widely used in the academic literature to evaluate the performance of aviation companies. Data Envelopment Analysis (DEA), in particular, is one of the most frequently used methods for measuring the relative efficiency of airlines and airports by considering multiple inputs and outputs (Cui & Yu, 2021). Indeed, Barros and Dieke (2008) conducted a comparative analysis of airport efficiency, while Merkert and Hensher (2011) demonstrated the impact of fleet planning and strategic management decisions on airline efficiency. According to academic research, such studies help the industry make more efficient use of resources, improve operational processes, and build stronger competitiveness.

Data Envelopment Analysis (DEA) is a non-parametric efficiency measurement method based on linear programming. This method evaluates the relative efficiency of similar decision units using multiple inputs and outputs (Charnes et al., 1978). The foundations of DEA are based on the generalization of the efficiency measurement defined by Farrell (1957) with a single input and a single output. Charnes, Cooper, and Rhodes (1978) developed Farrell's approach and introduced the first DEA model under the constant returns to scale assumption, known as the CCR model, into the literature (Charnes et al., 1978: 429-444). Subsequently, the BCC model, which takes into account variable returns to scale, was developed by Banker, Charnes, and Cooper and added to the literature (Banker et al., 1984).

While the CCR model measures total technical efficiency without distinguishing it from scale effects, the BCC model measures pure technical efficiency based on the assumption of variable returns to scale and reports the scale efficiency component separately. In other words, under the CCR model, it is assumed that the scale returns of units are constant, while under the BCC model, variable returns to scale are accepted (Budak, 2011). Constant returns to scale describe a situation where the rate of increase in inputs is equal to the rate of increase in outputs; if outputs increase at a higher rate than inputs, it is increasing returns, and if they increase at a lower rate, it is decreasing returns (Budak, 2011).

Within the DEA model, the performance of decision units can be analyzed either input-oriented or output-oriented. Input-oriented models focus on minimizing the inputs required to achieve a specific output level, while output-oriented models focus on how much outputs can be increased with existing inputs (Uygurtürk & Korkmaz, 2016: 413-414). In other words, input-oriented DEA calculates the extent to which an inefficient unit must reduce its inputs to achieve the same output, while output-oriented DEA determines the extent to which outputs can be increased with existing inputs (Uygurtürk & Korkmaz, 2016: 414).

Since the analysis objective of this study is to evaluate the potential of G20 countries to maximize their outputs with their existing resources in the aviation sector, the output-oriented DEA approach has been preferred. Table 3 summarizes the mathematical programming formulations of the CCR and BCC models in input/output-oriented formats. The solution of these models yields a technical efficiency score for each decision unit (total technical efficiency for the CCR model and pure technical efficiency for the BCC model). Additionally, the CCR and BCC scores are compared to calculate the scale efficiency value (Cooper et al., 2007). Scale efficiency indicates whether the decision unit is operating efficiently at its current scale (if equal to 1, it is scale efficient; if less than 1, it is not scale efficient).

Table 3. Input and Output Oriented CCR and BCC Models

Equation1- Input-Oriented CCR Model	**Equation2- Output-Oriented CCR Model**
$\min z_0 = \theta$ Constraints $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_0$ $\theta x_0 - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0 \quad j = 1, \ldots, n;$ $\lambda_0 \geq; \quad j = 1, \ldots, n;$ $r = 1, \ldots, s; \quad i = 1, \ldots, m;$	$\text{maks}\, z_0 = \theta$ Constraints $\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_0$ $\theta y_0 - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0 \quad j = 1, \ldots, n;$ $\lambda_0 \geq 0;$ $r = 1, \ldots, s; \quad i = 1, \ldots, m;$
Equation3- Input-Oriented BCC Model	**Equation4- Output-Oriented BCC Model**
$\min z_0 = \theta$ Constraints $\sum_{j=1}^{n} \lambda_j y_{rj} \geq y_0$ $\theta x_0 - \sum_{j=1}^{n} \lambda_j x_{ij} \geq 0$ $\sum_{j=1}^{n} \lambda_j = 1$ $\lambda_0 \geq; 0; \quad j = 1, \ldots, n;$ $r = 1, \ldots, s; \quad i = 1, \ldots, m;$	$\text{maks}\, z_0 = \theta$ Constraints $\sum_{j=1}^{n} \lambda_j y_{rj} \leq x_0$ $\theta y_0 - \sum_{j=1}^{n} \lambda_j y_{rj} \leq 0$ $\sum_{j=1}^{n} \lambda_j = 1$ $\lambda_0 \geq; 0;$ $r = 1, \ldots, s; \quad i = 1, \ldots, m;$

In a DEA study, defining decision units and their appropriate input-output variables is a critical step before beginning the analysis. Variables that serve the purpose of the study, have the power to influence performance, and can be reliably measured for each unit should be selected (Çınaroğlu et al., 2018). Additionally, the number of selected inputs and outputs must be proportional to the number of decision units. The rule proposed by Boussofiane et al. (1991) is that the number of decision units should be at least (m + p + 1) or

2(m + p)* times the sum of the number of inputs and outputs. In this study, a total of six input and output variables, three each, were included in the analysis for 18 countries. The fact that the number of decision units is above the recommended minimum level of (3+3)×2 = 12 indicates that a sufficient number of observations has been reached for the analysis and that a suitable structure has been provided in terms of the reliability of the results obtained (Boussofiane et al., 1991: 1-3).

The study focused on G20 countries. However, due to data access limitations, Russia could not be included in the study. Therefore, the analysis was conducted on the other 18 G20 countries, including Turkey. The 2023 aviation sector data for each country was obtained from the country reports titled “Value of Air Transport” published by the International Air Transport Association (IATA) (IATA, 2023). Three input variables and three output variables were used in the analysis. The input variables represent the basic resources and investments that countries have for their aviation sectors: Number of Commercial Airports (total number of commercial airports of civil/international status in the country), Aviation Investment (total public/private investment in aviation infrastructure in the relevant year, in millions of US dollars), and Total Number of Employees (total number of people employed in the aviation sector, in thousands). The output variables reflect the outputs generated by the aviation sector in that country and its sectoral performance: Annual Passenger Count (total number of passengers served at the country's airports in a year, including domestic and international flights, in millions of passengers), Cargo Transportation (annual cargo volume transported by air, in thousands of tons), Contribution of Aviation to the Country's Economy (direct + indirect contribution of the aviation sector to the country's gross domestic product, in millions of US dollars). These variables were chosen because they are regularly reported by IATA and ICAO and presented in a standard format for all countries. This ensures both data reliability and the ability to make sound comparisons across countries. Furthermore, the selected indicators align with the most frequently used metrics in academic studies on aviation efficiency. Of course, other variables such as fleet size, number of flights, fuel consumption, or connectivity indices could have been used. However, these data were not chosen because they are often not regularly shared, have different measurement methods across countries, or have a high degree of overlap with the selected indicators, leading to multicollinearity. Therefore, the study was conducted only with indicators that are regularly and reliably presented for all G20 countries.The definitions and scopes of these variables are detailed in Table 4.

Table 4. Description of the Input and Output Variables Used in the Study

Input Variables	Description
Number of Commercial Airports	The total number of civil/international commercial airports operating within the country.
Aviation Investment (Million USD)	The total amount of investment made by the country in aviation infrastructure and the sector in the given year

	(expressed in million USD). This includes airport construction, expansion, improvement projects, and other sectoral support.
Total Number of Employees (thousand persons)	The total number of personnel directly employed in the aviation sector (including airlines, airports, ground handling services, etc.).
Output Variables	
Annual Number of Passengers	The number of passengers carried in civil aviation within a year in the respective country (including both domestic and international flights). (Note: Reported in million passengers in IATA reports.)
Cargo-Mail Transport (thousand tons)	The total annual volume of freight and mail transported by air in the respective country (including both domestic and international services). (Note: Reported in thousand tons in IATA reports.)
Contribution of Aviation to the Country's Economy (Million USD)	The total economic contribution of the aviation sector to the country's economy or the direct plus indirect contribution to the country's GDP. This value represents the economic activity and added value generated by aviation.

This study has certain methodological and scope limitations. First, the analysis is based solely on IATA's publicly available “Value of Air Transport” data for 2023. Although IATA was contacted for data sets for other years, no response was received, and therefore time series comparisons could not be made. The analysis, conducted over a single year, does not allow for a sound comparison between the pre- and post-COVID-19 periods. Furthermore, fluctuations and transition effects that emerged in the post-COVID period may have been reflected in the results. In addition, despite being a G20 member, the Russian Federation did not share the necessary data for the relevant year with IATA and was therefore excluded from the sample. Russia's exclusion has resulted in a significant player in the global aviation market being left out of the assessment and has limited the integrity of the comparisons. For these reasons, the results obtained should be viewed as a relative assessment and should be supported by future research when access to more comprehensive and multi-year data sets is available.

The majority of the input and output variables used in this study were obtained from IATA's country based aviation reports. The number of commercial airports is defined by IATA as the total number of airports that host at least one scheduled flight per week and are open to commercial air transport. This data is presented under the "commercial scheduled flights" indicator and is based on OAG sources. The total number of employees refers to IATA’s definition of direct aviation employment, which includes airlines, airport operators, on-site businesses such as ground handling services, air navigation service providers (ANSPs), and manufacturers. Accordingly, ground handling and other on-site activities are also covered in this variable. Annual passenger numbers are defined as origin-destination (O-D) passenger departures within a country based on IATA's Direct Data Solutions (DDS) database and include both domestic and international passengers. The data represents total passenger departures recorded throughout the year. The amount of cargo carried represents the total air cargo tonnage passing through a country's airports and includes all civil air cargo, both sent and received. This data is generally sourced from Airports Council International (ACI). The sectoral economic contribution variable is evaluated solely based on the added value directly provided by aviation activities to the national economy. In IATA reports, this value is presented under the heading "direct economic output" and is often presented along with its share of the country's GDP. Therefore, all data used in this study were selected and interpreted in accordance with IATA's definitions.

To assess the suitability of the selected variables, correlations between inputs and outputs were examined prior to the analysis. Table 5 shows the Pearson correlation coefficients between input and output variables based on 2023 data.

Table 5. Correlation Coefficients Between the Input and Output Variables Used

Outputs \ Inputs	Commercial Airports	Investment	Total Employees
Annual Passengers	.424	.113	.478
Cargo	.898	.477	.943
Economic Contribution	.888	.179	.774

The results reveal a positive relationship between all inputs and outputs. In particular, the number of commercial airports is highly correlated with annual cargo volume (r=0.898) and economic contribution (r=0.888). Similarly, the total number of employees is strongly positively correlated with cargo (r=0.943) and contribution (r=0.774) outputs. This indicates a strong positive association between a country's infrastructure capacity and employment on the one hand, and its cargo volume and aviation value-added on the other. However, this is a correlation and not a proven causation. On the other hand, the correlation between the aviation investment variable and the number of passengers (r=0.113) and economic contribution (r=0.179) was found to be weaker. The relatively low relationship between the investment amount and outputs can be explained by the fact that the impact of investments on output productivity takes time or that investments made in some countries may not yield full returns by 2023. Overall, the correlation analysis supports the role of the selected inputs in the process of producing the relevant outputs; the fact that no input exhibits a negative or meaningless correlation with the outputs indicates that the variables selected are appropriate for the DEA model.

The correlation coefficient matrix for the input and output variables used is positive; in particular, strong relationships are observed between inputs such as the number of airports and total employees and outputs such as cargo volume and economic contribution. Low correlation values (e.g., investment and passengers) may indicate that there is no direct relationship between the relevant variable pairs or that indirect factors are present.

In this study, DEA was applied under both CCR (CRS) and BCC (VRS) assumptions, focusing on outputs. As a result of the analyses, total technical efficiency scores were obtained from the CCR model and pure technical efficiency scores from the BCC model for each country; additionally, scale efficiency was calculated by taking the ratio of these two values (Cooper et al., 2007). The results obtained are presented and discussed in detail in Section 4. For inefficient countries, reference country analyses based on the VRS model and input/output-based improvement ratios were conducted. Thus, it was determined where the performance gap of each inefficient country originated and how much improvement was needed in which variables to achieve full efficiency.

3.1. Analysis and Findings

In this study, the total technical efficiency values were calculated using the CCR model based on the assumption of constant returns to scale, and the pure technical efficiency values were calculated using the BCC model based on the assumption of variable returns to scale, in order to determine the relative efficiency levels of G20 countries in the aviation sector. The analyses were performed using DEAP 2.1 software with an output-oriented model structure, and the findings were interpreted in detail.

First, the efficiency scores of the countries were calculated to identify efficient and inefficient decision-making units. The inefficient countries were identified, along with the weight coefficients, to determine which efficient countries they could use as references to improve their performance. In the final stage, the potential improvement rates that these countries needed to achieve at the input and output levels to reach the efficiency frontier were calculated.

3.1.1. Countries' 2023 Efficiency Scores

In this analysis, the efficiency levels of the aviation sectors of the G20 countries were calculated using the output-oriented CCR model (Equation 2) and the output-oriented BCC model (Equation 4).

Output-oriented CCR and BCC models were used in the activity analysis of the aviation sectors of G20 countries. Through these models, the aim was to obtain the highest level of aviation output (annual passenger traffic, cargo volume, and sectoral economic contribution) that each country could achieve with its current resources (inputs such as investments, number of employees, and airport infrastructure). The main reason for choosing output-oriented models is that countries have limited control over inputs such as aviation investments in the short term. In addition, variables such as the number of employees and the amount of investment are considered indicators of a country's level of development, and therefore reducing such inputs is not considered an appropriate strategy. Output-oriented models (Equations 2 and 4) were preferred in this study, while input-oriented models (Equations 1 and

3) were not applied because countries have limited short-term control over inputs such as investments and employment.

In this context, three key efficiency values were considered in the analysis: total efficiency based on the constant returns to scale assumption (CCR), technical efficiency based on the variable returns assumption (BCC), and scale efficiency calculated as the ratio of these two models (CCR/BCC). While the CCR model measures the overall efficiency of countries, the BCC model reveals technical efficiency by comparing countries with similar structures. Scale efficiency, on the other hand, makes it possible to assess whether a country manages its aviation sector in a structure appropriate to its scale. Thus, the efficiency of each country can be analyzed not only in terms of outputs but also in terms of the appropriateness of the scale at which it operates.

Table 6 shows the efficiency (CCR), technical efficiency (BCC), and scale efficiency (CCR/BCC) scores of G20 countries for 2023 based on fixed return assumptions. Countries' efficiency scores range from 0 to 1, with 1 indicating full efficiency. A country's efficiency score of 1 indicates that it is using its resources most efficiently in the aviation sector and has achieved the highest possible output with the available inputs. This means that the country's current performance has reached the highest theoretical level it can achieve. On the other hand, an efficiency score below 1 indicates that the country in question is not using its aviation resources at full efficiency and is falling short of its potential performance level (Avcı and Aktaş, 2017). This situation reveals that the country in question has the capacity to produce higher levels of output with its current infrastructure, capital, and labor force, but is unable to fully realize this potential.

Table 6. DEA Efficiency Results of G20 Countries (2023)

Country	**CCR**	**BCC**	**CCR/BCC**	**Country**	**CCR**	**BCC**	**CCR/BCC**
Argentina	0.833	1.000	0.833	**India**	0.364	0.584	0.622
Australia	0.487	0.490	0.995	**Italy**	0.898	1.000	0.898
Brazil	0.559	0.676	0.826	**Japan**	0.729	0.767	0.951
United Kingdom	1.000	1.000	1.000	**Canada**	0.600	0.606	0.990
China	0.684	1.000	0.684	**Mexico**	0.895	0.903	0.990
Indonesia	1.000	1.000	1.000	**Saudi Arabia**	0.684	0.686	0.998
France	0.998	1.000	0.998	**Turkey**	1.000	1.000	1.000
South Africa	0.499	1.000	0.499	**Germany**	1.000	1.000	1.000
South Korea	1.000	1.000	1.000	**United States**	1.000	1.000	1.000

When the constant returns to scale efficiency scores (CCR) are examined, it is concluded that as of 2023, eleven countries (the United States, Germany, the United Kingdom, Turkey, China, France, South Korea, Indonesia, Argentina, Italy and South Africa) were fully efficient in terms of overall efficiency. According to the CCR model, India was identified as the country with the lowest overall efficiency score, with a value of 0.364.

Considering the variable returns to scale efficiency scores (BCC), it is observed that in the same year, twelve countries (the United States, Germany, the United Kingdom, Turkey, China, France, South Korea, Indonesia, Argentina, Italy, South Africa and Japan) were found to be fully efficient in terms of technical efficiency. According to the BCC model, India had the lowest technical efficiency score, with a value of 0.584.

In terms of scale efficiency scores, it was found that as of 2023, eleven countries (the United States, Germany, the United Kingdom, Turkey, China, France, South Korea, Indonesia, Argentina, Italy and South Africa) operated at an appropriate scale in their aviation sectors and therefore achieved scale efficiency. When scale efficiency scores are taken into account, India is seen to have the lowest scale efficiency with a value of 0.622. This situation shows that India is unable to use its current aviation infrastructure in a structure appropriate to its scale and therefore experiences a loss of efficiency in the use of resources.

Table 7. Efficiency Status of the Countries in the Study for the Year 2023

Country	Efficiency Status	Country	Efficiency Status
Argentina	**Efficient**	**India**	Inefficient
Australia	Inefficient	**Italy**	**Efficient**
Brazil	Inefficient	**Japan**	Inefficient
United Kingdom	**Efficient**	**Canada**	Inefficient
China	**Efficient**	**Mexico**	Inefficient
Indonesia	**Efficient**	**Saudi Arabia**	Inefficient
France	**Efficient**	**Turkey**	**Efficient**
South Africa	**Efficient**	**Germany**	**Efficient**
South Korea	**Efficient**	**United States**	**Efficient**

Upon examining Table 7, it is observed that as of 2023, the countries that achieved full efficiency in the aviation sector among the G20 members are the United States, Germany, the United Kingdom, Turkey, China, France, South Korea, Indonesia, Argentina, Italy and South Africa. In contrast, Australia, Brazil, India, Japan, Canada, Mexico and Saudi Arabia remained below the full efficiency threshold during this period. India, in particular, stands out by recording the lowest scores across all types of efficiency. On the other hand, it is understood that countries such as Canada, Mexico and Japan, while approaching technical efficiency, were unable to fully achieve scale efficiency.

The United States, South Korea, Germany, and Turkey are among the efficient G20 countries. In the United States, a wide airport network, an open airline market, and the use of technology have supported economies of scale (Bazargan & Vasigh, 2003). In South Korea, government planning and investments, such as the expansion of Incheon, raised efficiency, while support for low-cost airlines expanded the market (Hong, Cho & Yoon, 2024). Germany's strong logistics system and close link with industry also improved performance (Martí, Martín & Puertas, 2017). Bloom and Van Reenen (2010) showed that management practices explain many of the differences in productivity between countries. In Turkey, large partnership projects, better management, and reforms in regulation, together with its location, have helped the country appear as efficient in the DEA results.

India, Brazil, Canada, and Australia face different challenges. In India, fast growth in demand has not been matched with enough infrastructure and staff, so low-cost carriers operate more efficiently than full-service airlines (Saranga & Nagpal, 2016). In Brazil, more than 50 billion Brazilian Reais (BRL) have been invested in airports, but market use is still low and many people have never flown, which reduces efficiency (Carvalho, 2025). In Canada, the country's large size, tough weather, and small communities in remote regions make air travel costly and limit competition (Competition Bureau Canada, 2025). In Australia, long distances and low passenger numbers make it hard for many regional airports to operate in a sustainable way, which keeps investments from turning into higher efficiency (Ninesquared, 2024).

3.1.2. Reference Set and Weight Values

In Data Envelopment Analysis, a reference set is defined for each inefficient decision unit. This reference set consists of decision units that are considered relatively efficient in the analysis and is used as an example to enable the inefficient unit to reach its efficiency frontier. Efficient decision units are assigned as references to inefficient countries with specific weight coefficients; thus, it is determined which countries inefficient countries should emulate in terms of performance structure (Acer & Timor, 2017: 345). However, it should be noted that the full efficiency of an airport does not mean that its performance is at an ideal level; it only indicates that it has the best performance relative to other airports included in the analysis (Avcı & Aktaş, 2016).

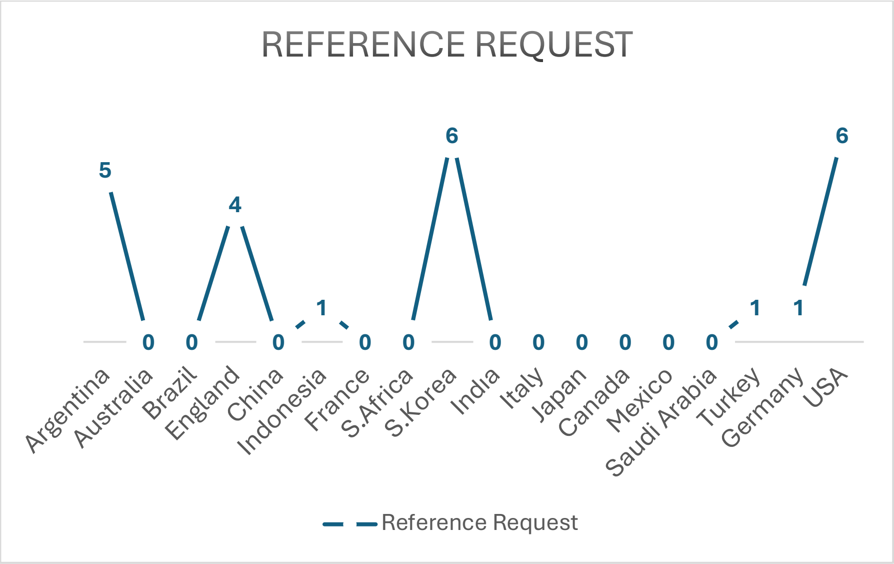
In this context, after identifying the inefficient countries in the analysis using the output-oriented CCR model (Equation 2), an assessment was made of which efficient countries these countries should use as references in order to improve their aviation performance and reach the efficiency frontier as determined by the output-oriented BCC model (Equation 4). The reference countries and the assigned weight values indicate which decision-making units' operational structures each inefficient country should emulate in order to increase its technical and scale efficiency.

Table 8. Reference Sets and Weight Assignments of the Countries

Inefficient Countries	Reference Set and Weight Values
Australia	S.Korea (0.727) United States (0.021) Argentina (0.171) United Kingdom (0.081)

Brazil	Indonesia (0.369) Turkey (0.066) United States (0.041) Argentina (0.525)
India	S.Korea (0.687) United States (0.092) United Kingdom (0.221)
Japan	S.Korea (0.698) United States (0.087) Germany (0.215)
Canada	S.Korea (0.108) United Kingdom (0.349) United States (0.048) Argentina (0.495)
Mexico	S.Korea (0.792) Argentina (0.159) United States (0.049)
Saudi Arabia	S.Korea (0.769) United Kingdom (0.148) Argentina (0.083)

Table 8 presents the reference sets assigned to the inefficient countries for the year 2023 along with the corresponding weight values. Upon examining the table, it is observed that, for example, India should take countries such as South Korea, the United Kingdom and the United States as references in order to achieve efficiency. The weight values assigned to India in the relevant year are 68.7 percent for South Korea, 22.1 percent for the United Kingdom and 9.2 percent for the United States. This indicates that it would be appropriate for India to model its operational structure and performance on these three countries in order to improve its technical efficiency.



Shape 1. Number of Times Countries Were Used as References

According to the "Number of References Used by Countries" chart, South Korea, India, and the United States were the most frequently cited countries, receiving a total of 6 references. Argentina follows with 5 and Australia with 4. Other countries were referenced either 1 or 0 times.

Among the decision-making units analyzed based on this data, South Korea and the United States stand out as models for many countries in terms of technical and scale efficiency. This indicates that both countries exhibit high performance in data envelopment analysis and are frequently included in the reference set.

3.1.3. Potential Improvement Rates

Through the Data Envelopment Analysis (DEA) model, attainable performance targets are established for inefficient decision-making units to help them reach the efficiency frontier. Potential improvement rates were calculated through output-oriented DEA models (Equations 2 and 4). These target values are referred to in the literature as "potential improvement" (PI). Potential improvement rates represent the proportional change required for a given input or output variable to reach its targeted level from its current state (Uzgören and Şahin, 2013). The formula for calculating potential improvement is as follows:

Equation 5. Potential Improvement Rate Formula

$$((Target\ Value - Actual\ Value) \times 100)/(Actual\ Value)$$

In order for inefficient countries to reach the efficiency frontier, output variables with positive potential improvement (PI) values must be increased by the indicated rates, while input variables with negative PI values must be reduced accordingly. This means that output improvements follow the logic of the output-oriented models (Equations 2 and 4), whereas input reductions correspond to the approach of the input-oriented models (Equations 1 and 3). If any input or output variable of a country has a PI value equal to zero, this indicates that no improvement is required for that specific variable (Özden, 2009).

However, it is important to emphasize that a unit being evaluated as efficient (1.000) in DEA does not mean that it has the best possible performance in absolute terms. A fully efficient airport is not necessarily operating at an ideal performance level, but rather it exhibits the best relative performance among all evaluated units. Therefore, in an environment where performance levels are generally low, a relatively better-performing unit may appear fully efficient. Likewise, a unit with the lowest efficiency score should not automatically be considered a failure in absolute terms.

Based on the Potential Improvement Rate Formula (Equation 5), the target values and proportional changes for inefficient countries were calculated and are presented in Table 9.

Table 9. Target Values and Potential Improvement Rates for Inefficient Countries

AUSTRALIA			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	17500000	35747000	+104,27%
Cargo	1000000	3057000	+205,70%
Contribution to Economy	13100000000	26759530000	+104,96%
Number of Commercial Airports	161	36	−77,64%
Aviation Investment	3500000000	3500000000	0,00%
Total Employees	162600	162600	0,00%
BREZIL			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	11100000	16414000	+47,43%
Cargo	1400000	2070000	+47,86%
Contribution to Economy	2500000000	26818332000	+972,73%
Number of Commercial Airports	169	94	−44,38%
Aviation Investment	600000000	600000000	0,00%
Total Employees	246800	246800	0,00%
INDIA			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	33900000	58015000	+71,19%
Cargo	3300000	5647000	+71,12%
Contribution to Economy	5600000000	61816680000	+1003,87%
Number of Commercial Airports	116	83	−28,45%
Aviation Investment	1200000000	4078549000	70,55%
Total Employees	369000	369000	0,00%
JAPAN			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	34400000	47786000	+38,96%
Cargo	4600000	6000000	+30,43%
Contribution to Economy	20000000000	59073956000	+195,37%
Number of Commercial Airports	75	75	0,00%
Aviation Investment	5000000000	4313916000	−13,72%
Total Employees	359000	359000	0,00%
CANADA			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	31600000	52145000	+65,00%
Cargo	1300000	2864000	+120,31%
Contribution to Economy	23000000000	37953357000	+65,01%
Number of Commercial Airports	229	71	−68,99%
Aviation Investment	2000000000	2000000000	0,00%
Total Employees	265000	265000	0,00%
MEXICO			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	27200000	31805000	+16,91%
Cargo	1200000	3993000	+232,75%
Contribution to Economy	33200000000	36746603000	+10,66%
Number of Commercial Airports	57	51	−10,53%
Aviation Investment	3700000000	3700000000	0,00%
Total Employees	202000	202000	0,00%

SAUDI ARABIA			
Input/Output Variable	**Actual Value**	**Target Value**	**Potential Improvement Rate (%)**
Annual Passengers	28600000	41686000	+45,79%
Cargo	713000	2600000	+264,25%
Contribution to Economy	14300000000	20843048000	+45,78%
Number of Commercial Airports	28	23	−17,86%
Aviation Investment	5000000000	3699260000	−26,01%
Total Employees	141000	141000	0,00%

The analysis results show the target values for input and output variables for inefficient countries and the improvement rates required to achieve these targets in Table 9. For example, in order for Australia to achieve an efficient structure, it must increase its annual passenger numbers from 17.5 million to 35.7 million (a 104.3% increase), increase the amount of cargo transported from 1 million tons to 3.06 million tons (a 205.7% increase), and increase aviation's contribution to the country's economy from 13.1 billion US dollars to 26.8 billion dollars (a 104.9% increase). In contrast, a reduction of approximately 77.6% in the number of commercial airports is recommended. These findings indicate that Australia needs to centralize its aviation infrastructure and avoid excessive dispersion in order to use its current resources more effectively.

Similarly, comparisons were made between current and target values for Brazil, India, Japan, Canada, Mexico, and Saudi Arabia, and concrete improvement recommendations were developed for each country that decision-makers can utilize.

4. CONCLUSION and DISCUSSION

According to the findings, 11 out of the 18 analyzed countries were found to be 100 percent technically efficient, while 7 countries fell below the efficiency frontier. For instance, the United States, Germany, the United Kingdom, Turkey, China, France, and South Korea all came out as efficient under both models. These countries share some common traits, such as strong aviation infrastructure and operating at a scale that allows them to use resources more effectively than many of their peers. This points to a recurring pattern among the efficient countries, but it should not be taken to mean that infrastructure alone is the direct reason for their efficiency. On the other hand, countries such as Australia, Brazil, India, Japan, Canada, Mexico, and Saudi Arabia have performed poorly in certain output variables and fallen below the efficiency frontier.

Our findings are close to earlier studies. Tunç et al. (2024) found that big economies like the United States worked at full efficiency, and in our results the United States and South Korea also stand out. Martí et al. (2017) pointed out that countries with better logistics systems perform better, which fits with our finding that Germany, the UK, and China are fully efficient.

For Turkey, past research also supports our conclusion. Koçak (2011) and Avcı & Aktaş (2016) found that several Turkish airports worked efficiently, while Yılmaz et al. (2022) underlined the role of external factors. These studies help explain why Turkey as a whole is fully efficient in our analysis.

There are some differences too. Mhlanga (2020) found problems with South Africa's state airlines, but our results show the country as fully efficient, probably due to changes after the pandemic. In India, Saranga & Nagpal (2016) found only low-cost airlines were efficient; we also classified India as inefficient overall.

In general, our study confirms the main patterns seen in earlier work. Where results differ, this is mostly because of different years, methods, or variables used.

An analysis of the reference sets created for inefficient countries revealed that South Korea was the most frequently cited reference. This suggests that South Korea serves as a benchmark for many countries in terms of both technical and scale efficiency. Furthermore, the specific input and output variables requiring improvement in the inefficient countries were identified through potential improvement rates. In particular, substantial improvements were found to be necessary in variables such as air cargo volume and aviation's contribution to the national economy.

One notable finding of the study is that the BCC model classified more countries as efficient compared to the CCR model. This outcome indicates that the assumption of variable returns to scale reflects structural differences among countries more flexibly. Nevertheless, it should be acknowledged that the concept of efficiency is contextual, and different results may emerge if the set of decision-making units included in the analysis changes.

In this regard, future studies may focus on more specific components of the aviation sector (such as air cargo only, domestic passenger transport only, or staff productivity) to conduct more targeted efficiency analyses. Additionally, where data availability permits, it is recommended to conduct longitudinal comparative analyses and examine productivity changes over time using the Malmquist index method.

The findings obtained from this research are expected to provide valuable insights for shaping aviation policies in G20 countries, restructuring infrastructure investments and developing output-enhancing strategies. In particular, by adopting the structural characteristics of the efficient countries they are referenced to, the inefficient countries may take strategic steps that can contribute significantly to improving the efficiency of their national aviation sectors.

DEA is a tool that measures relative efficiency and compares countries, but it does not explain cause and effect. A country with a score of 100 percent in this study is simply performing better than the other G20 countries in how it turns inputs into outputs. This does not mean the country has reached a perfect level or that one specific policy directly caused the result. DEA only shows which countries are on the efficiency frontier based on the available data. For this reason, efficiency scores and correlations should not be seen as proof of causation. Mentions of policies or practices can be treated as possible explanations or starting points for further research, not as final conclusions. Overall, the results show which countries are efficient, but they do not explain the reasons behind it. Understanding those reasons would require more detailed statistical and empirical studies.

The DEA findings of this study show that efficient countries stand out due to strong infrastructure, scale suitability, and the ability to convert resources into higher passenger, cargo, and economic outputs. In contrast, inefficient countries face constraints such as low cargo and economic performance, mismatches between infrastructure and demand, and scale inefficiencies.

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