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Airline’s business performance indicators and their impact on operational efficiency

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ABSTRACT

Airlines must constantly evaluate the costs and efficiency of their operational performance indicators to establish a competitive business market strategy. This study aims to investigate the relevance of some performance indicators of airline´s management and operational efficiency. With the use of a panel data regression for the four largest private Brazilian airlines – Avianca, Azul, Gol, and Latam, from 2009 to 2017, the results show that operational efficiency is achieved when there is a greater offer of routes and flight frequency to meet passenger demand, generating higher revenue passenger kilometer (RPK). On the other hand, shorter stage length and reduced takeoff numbers affect inversely proportional the operating efficiency as a function of fuel consumption and energy capacity. Through the analysis of these performance indicators, it is possible to determine strategies that support decision making to increase the operational efficiency of airlines.

KEYWORDS

Air Transport, Business strategies, Competitiveness, Operations

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1. INTRODUCTION

Air transport companies arouse the interest of stakeholders with their usual operations, infrastructure, investment, and operational capacity to meet the growth of passenger traffic and, at the same time, obtain financial return for companies. According to ICAO (2018), aviation reached a record of 4.3 billion passengers on scheduled services in 2018, a 6.1% increase over 2017. It also predicts a steep increase in world passenger traffic in 18 years (2016-2034), expressed in terms of revenue passenger kilometer (RPK), surpassing 14 trillion RPK, with the growth of 4.5% per year.

Additionally, the tourism sector represented 7.7% of the Brazilian GDP in 2019, when Brazil had 15 airlines (commercial airlines based in the country) operating in 121 commercial airports and handling 108.9 million passengers in 861.1 thousand flights (ATAG, 2020). The four largest Brazilian airlines in 2017 (Avianca, Azul, Gol, and Latam - in alphabetic order) are private companies operating both domestic and international flights. In terms of strategy, the company Azul self-declares as a low-cost carrier (LCC), combined with a regional carrier business model (RGC), Gol operates with a mix between LCC and full-service carriers (FSC), Avianca, which had operations in the Brazilian domestic market suspended in the first half of 2019, operated until then with a RGC regime and increasing the LCC, and Latam operates at the FSC regime and has been increasing the RGC (Oliveira et al., 2021).

The manageability of airlines, considered key players in air transport, can be improved by determining actions to increase operational efficiency through flight operations management, allowing companies to benefit from efficient air transport management. The process that determines the positive effects of optimal operation incorporates analyzes of strategic flight operation management. Through these analyzes, it intends to look for ways to optimize resources through strategic planning that, according to Mintzberg et al. (2010), have the purpose of mapping the organization's guidelines, promoting the coordination of activities, strengthening policies, and carrying out decision making. This type of analysis can avoid the "Icarus paradox" for airlines, when overconfidence from past successes leads to a lack of good strategy (Kumar, 2020).

External influences, such as oil price fluctuations, economic crises, and technological advances, as well as the change in the aeronautics sector itself, such as the entry of low-cost carriers (LCCs), alliances, mergers, and market deregulation result in challenging strategies for face competition in the aviation market. Challenges faced in the air transport sector drive airlines to focus on operational efficiency and cost management (Joo & Fowler, 2014). The cost reduction strategy, for both consumers and airlines, is the result of efficient flight operations, which tend to minimize costs from selling tickets online all the way up to efficient use of airspace.

Studies examiningairline operations play a crucial role in developing efficient management models for the airline business. These models impact on corporate revenues and focus on operational efficiency (Lozano & Gutiérrez, 2011; Kottas & Madas, 2018; Cox et al., 2018), energy efficiency (Babikian et al., 2002), and technical efficiency (Merkert & Hensher, 2011; Sakthidharan & Sivaraman, 2018), while this study provides an analysis of relevant indicators to the management of air operations that can provide better operational efficiency of airlines, as presented by Saranga and Nagpal (2016). However, studies that address the identification of factors and their impact on operational efficiency are still necessary. As a result of these gaps, in scientific terms, the following research questions arise: what are the possible variables that best describe the airlines' performance and operational efficiency indicators? What are the possible covariance relationships between such variables to support the hypothesis of a relationship between the set of variables? What is the intensity and direction of the presumed cause-and-effect relationships of a given stochastic model?

Therefore, the objective of this study is to examine the relevance of these performance indicators in airline's operational efficiency. As a contribution, the research findings can be useful as a reference for the air transport industry, and airlines planners and managers, in the decision-making process that harmonizes some of the conflicting indicators for better company performance on operational efficiency.

2. BRAZILIAN AIRLINE INDUSTRY

Brazil is the largest economy in Latin America and its continental size makes for profitable conditions to attract airlines, traffic volumes, and potential stakeholders to the dynamic air transport market with expected growth in number of passengers for the upcoming years. The country has 556 public aerodromes and 2,183 private aerodromes recognized by its regulatory agency, being that only 168 of these (6%) are used to commercial aviation (ANAC, 2020).

Considering an analysis applied in this study from 2009, the four largest private airlines in Brazil are Avianca, Azul, Gol and Latam. It is noteworthy here that, in May 2009, Avianca ceased its flight operations by ANAC due to security risks and unbalances after the company requested judicial recovery in December 2018. These four airlines, at the time of this study, operated in the major cities where they were able to process increasing passenger movement, demonstrated by the increase of available seat kilometer (ASK) on both domestic and international flights, rising 49.7% and 51.6%, respectively, in the last 10 years (ANAC, 2018).

To better understand the industry context of the airline industry in Brazil, Table 1 provides a brief profile of the airlines presented which include the number of aircraft owned, manufacturers, number of serviced location and the number of staff employed from 2009 to 2017.

Azul began its operations in December 2008 with the Embraer 195/190 and, in 2011, added the ATR-72-200/600 to its operations. Gol operates with a homogeneous fleet using only Boeing (Boeing 737-300, 737-700, 737-800, 767-200, 767-300), while Avianca operated with the aircraft Embraer 120 and Fokker 100. In 2010, the airline added Airbus 319 and in 2012, withdrew the Embraer 120 from operation, bringing the Airbus family - 318/19/20 to its fleet. Latam operated the Airbus family - 319/20/21/30/40 and Boeing 767/ 777.

Aircraft are taking off and landing several times a year. As a result, the four companies have several serviced locations in the country, with a few employees by aircraft proportional to the type of the airline operation. As usual, cargo companies have a smaller administrative structure, while passenger transport companies need more complex administrative structures, and a larger number of employees. A smaller number of employees per aircraft represent the most efficient use of the workforce per unit of capital (ANAC, 2018).

3. AIRLINES OPERATION MANAGEMENT

The airlines' worldwide transport capacity grew by 6.0% ASKs during 2018, resulting in a PLF record global average of 81.9% (ICAO, 2018). From this perspective, airlines seek to match the growth in passenger demand by increasing flight frequency or using larger aircraft. Increasing flight frequency generally leads to increased operating costs, however, increases the quality of service, and by using larger aircraft, the cost per seat of airlines is reduced (Kölker et al., 2016).

Table 1
Airline industry in Brazil

Airline	Year	Number of aircraft	Manufacturers	Number of serviced location	Staff employed
Avianca	2009	19	Embraer and Fokker	22	1609
	2010	22	Embraer, Fokker, and Airbus	19	1867
	2011	31		26	2635
	2012	32	Airbus and Fokker	26	3200
	2013	38		29	3664
	2014	48		31	4280
	2015	51		29	4283
	2016	43	Airbus	28	4553
	2017	44		28	5354
Azul	2009	14	Embraer	14	1516
	2010	26		24	2932
	2011	49	Embraer and ATR	45	4352
	2012	61		61	5000
	2013	56		106	8204
	2014	151	Embraer, ATR, and Airbus	112	10843
	2015	151		107	10467
	2016	124		109	10221
	2017	124		102	11184
Gol	2009	127	Boeing	49	17963
	2010	123		49	18776
	2011	122		56	18781
	2012	126		57	16000
	2013	147		56	16183
	2014	141		60	16186
	2015	139		59	15812
	2016	128		58	15129
	2017	125		57	12181
Latam	2009	132	Airbus and Boeing	43	22414
	2010	146		44	24729
	2011	156		48	28808
	2012	158		46	29000
	2013	203		44	27760
	2014	163		45	27742
	2015	168		48	25627
	2016	165		49	22929
	2017	162		47	21853

Source: Research data.

Using the frequency-capacity model, called Forecast of Aircraft Movements, Kölker et al. (2016) make predictions of aircraft movement growth. The purpose is to adjust flight capacity and frequency as a strategy to anticipate capacity and operations constraints. Park and Kelly (2018) examine the ideal fleet according to aircraft cost-effectiveness variability by size, market segment, and operating constraints, although do not consider that airlines optimize their costs and revenues, such as making collaborative alliances, for instance.

Studies such as Givoni and Rietveld (2010) demonstrate that the choice of aircraft size is influenced by route characteristics such as distance, level of demand, and competition. Even with environmental consequences, on flight management prevails frequency adjustment over increasing aircraft size, influenced by the high demand market with strong competition. However, by reducing the frequency of flight service for short-haul routes, passengers who do not have time availability are disadvantaged.

Capability analysis to meet local demand represents the strength that airlines exert within a region. Thus, even without quantifying the demand on a route, Pai (2010) assesses determinants of aircraft size and flight frequency in the US market. The income level of the traveler has a significant effect on flight frequency, as the wealthiest people value their time more and thus require higher flight frequency and less delay. Thus, from the perspective of strategic operational management, the longer route distance decreases the flight frequency, but impacts the choice of larger aircraft.

To provide greater flexibility in flight operations to serve different locations, Husemann et al. (2018) evaluate the criteria for deciding which aircraft to use on certain routes considering the paid cargo loaded and flight distance. The authors demonstrate that airlines with greater flexibility have higher operating costs by employing oversized aircraft in their daily operations, resulting in higher fuel consumption and higher operating costs.

In addressing fleet management in the Chinese market, Wang et al. (2014) estimate that the rapid growth of Chinese air traffic was due more to increased flight frequency than to increased aircraft size. This is a result of the market concentration that affect flight frequency, leading to increased competition among airlines, which results in improved quality of service and increased volume of air traffic.

Regarding the decision to expand or reduce flight operations, Hsu et al. (2011) applied Grey's topological forecasting method combined with the Markov chain model to predict passenger traffic and capture the randomness of demand. The authors determine an optimal aircraft replacement schedule, considering various scenarios, according to cyclical and dynamic demand. However, the uncertainty period was assumed only in the first two scenarios, and the aircraft replacement planning was done for a short period, reportedly financially unviable.

By providing a generalized aircraft trip cost function, Swan and Adler (2006) demonstrated that flight management is following operating cost, proportional to hours flown, whereas stage length and fuel burn are in accordance with the aircraft size or its seating capacity and weight. However, when analyzing unit cost parameters as a function of distance and aircraft size, the authors do not consider other operational performance indicators, such as ASK, RPK, and offered routes, which could affect travel efficiency.

In the strategic operational management process, the decision on which aircraft to operate a certain route network is the subject of analysis by Repko and Santos (2017). Using a multi-period modeling approach, the authors demonstrate that the ideal aircraft for certain routes adjusts as the potential demand develops for that period, but do not consider demand variation for different routes, nor assess the impact of the adopted routes on the operational efficiency of airlines.

Complementary, Dozic and Kalic (2015), in turn, adopt a model for planners and managers to jointly decide on the type and size of an airline's fleet and apply it to a hypothetical airline at Belgrade Nikola Tesla Airport (BEG). However, this management model is only valid for small and medium demand markets.

To assess the effects of operations management, Krstić Simić and Babic (2015) demonstrated that changes in air traffic management and airport infrastructure, such as runway augmentation, would improve the operational performance of the airport system, directly affecting flight operational efficiency. Nonetheless, the suggested airport structural changes would require a high financial investment. Thus, determining operational efficiency factors capable of improving the strategic management of airlines becomes necessary to minimize cost and expenses and strengthen competitiveness among companies.

4. AIRLINES OPERATIONAL EFFICIENCY

To survive in competitive environments and under economic pressures, airlines must constantly evaluate the efficiency of their air operations. When dealing with studies in the literature on airline operating efficiency, Stroup and Wollmer (1992) propose a linear fuel management model program, based on price and station and supplier constraints, whereby fuel costs can be reduced and increase profit on different aircraft models.

Analyzing the effects of aircraft operating costs on an airline, Bießlich et al. (2018) apply a hierarchical metamodeling approach that measures the profitability and price of air tickets based on the direct operating cost (DOC) model. After costing, airlines decide on aircraft orders, perform route adaptations, and propose changes to the business model. Yet, the model overestimates total operating costs and does not determine the operating efficiency factors that can influence airlines' economic gains.

Research in the literature addresses more than one type of efficiency in its analysis. Using a multiobjective DEA approach, Lozano and Gutiérrez (2011) estimate that eight out of seventeen airlines adopted in the model have technical efficiency, and four out of them achieved production scale efficiency. However, data limitation, such as the use of fuel cost instead of fuel consumption to fuel metering may have undermined the result of the analysis.

Applying a two-stage DEA approach, with partially bootstrapped random-effects Tobit regressions in the second stage, Merkert and Hensher (2011) demonstrate that the mix of the fleet, such as the A320 versus A380, have a significant impact on technical, allocative, and cost-efficiency of airline efficiency. Plus, the airline and aircraft size have a positive impact on the three types of efficiencies addressed. Aircraft size and flight distance are directly related to environmental impact per kilometer (Cox et al., 2018). Even though, operating aircraft have less impact than fuel production.

Incorporating operational and financial aspects into the input and output of the DEA model, the research conducted by Kottas and Madas (2018) assesses the comparative efficiency of the alliance members of 30 major international airlines. An alliance of airlines, sharing large freight revenue, is more efficient than those showing low freight traffic volumes because they have improved profitability and increased freight revenue flow. Nevertheless, to circumvent the problem of data scarcity, the authors did not consider ATK, a key variable for the model.

Studies such as those conducted by Yu et al. (2017) analyze the dynamic efficiency of a range of airlines from various countries by combining a two-stage dynamic network data envelopment analysis (DNDEA), with a bootstrapped truncated regression model for the period from 2009 to 2012. The survey results show that overall operating efficiency presents an annual downward trend, and airline alliances have a negative impact on companies' operating performance due to insufficient collaboration among members.

Joo and Fowler (2014) employ DEA with Tobit regression analysis to assess comparative operating efficiencies of 90 airlines in Asia, Europe, and North America. Even with limited data, which requires further research, the authors clarify that airline efficiency in Europe is the lowest among airlines in these three regions, while differences in the efficiency of US and Asian airlines were not significant. From the analysis of the technical efficiency of 11 US airlines, combining operational and financial data for the period 1998-2010, the DEA B-Convex model implemented by Barros et al. (2013) finds that the carriers analyzed have a reasonable level of efficiency. Also, time has a positive influence on the efficiency of US airlines, as time goes on, they become more competitive organizations.

Analyzing the static efficiency and dynamic productivity changes of 14 carriers from 2006 to 2015 using the dual bootstrap DEA approach, Choi (2017) demonstrated that most LCCs have relatively low efficiency and productivity. Airlines mergers are an alternative to reducing overall operating costs, enhancing the network synergy effect, and achieving economies of scale.

Approaching the short period of 2013 and 2014, Sakthidharan and Sivaraman (2018) present estimates of technical efficiency between 70% and 90% and show that the efficiency of scale is increasing as the Indian airline sector expands. The study also shows that the cost of maintenance and labor cost have a heavy chunk on the operating cost of airlines. Besides, the LCC model is better suited than the FSC in India, given the improved operating efficiencies found in homogeneous and new fleets, resulting in lower maintenance costs.

Through an econometric model of multiple regression analysis, Singh et al. (2019) demonstrate that operating larger aircraft and increasing the payload has a positive effect on operating cost efficiency. Besides, a longer stage length is beneficial to reducing expenses. However, that study does not use key variables, such as ASK, operating cost and expense, and the number of aircraft and manufacturers to analyze the operating efficiency of airlines.

Complementing the theme proposed in this study, Saranga and Nagpal (2016) investigate the driving factors of operational efficiencies and their impact on airline market performance. The authors proposed a theoretical framework that links various structural, executional and regulatory drivers to airline efficiency. Even not using PLF in the second stage for the regression analyses, due to high correlation with other independent variables, resulting in multicollinearity, the results presented by the authors indicates that some of the structural and regulatory factors have an unwelcoming impact on airline performance, while technical efficiency is a key factor to gain market power.

From the variables found in the literature, Table 2 presents the summary of those, which can measure some types of efficiencies.

These variables collected from the literature and presented in Table 2 have been used in the studies to evaluate efficiency. It is noted that operational efficiency studies have mentioned operational indicators such as RPK, ASK, PLF, stage length, fuel cost, operating cost and expense, operating revenue, number of aircraft in operation, and their manufacturers and flown routes.

Table 2
Summary of operational efficiency variables

Author	Type of efficiency	Variables	Measurement forms
Lozano and Gutiérrez (2011)	Operational	Fuel Cost	TON x KM
		Flight and Ground assets	n
		Operating Cost	€
		RTK	TON x KM
Joo and Fowler (2014)		Revenues	USD
		Passengers	n
		RPK	million x KM
		PLF	percentage
		Expenses	USD
Choi (2017)		PLF	%
		CASM	million x mi
		RASM	million x mi
		Passenger yield	million x mi
		Fuel Expense	USD
		Passenger Revenue	USD
		Full-time Employee Equivalents	n
		Total Operating Revenue	USD
Kottas and Madas (2018)		Employees	n
		Operating costs	USD
		Number of Aircraft	n
		Revenue	USD
		RPK	million x KM
		RTK	million x KM
Yu et al. (2017)	Dynamic operational	Size of Leased Fleet	n
		Labor Expenses	US$
		Fuel Expenses	US$
		Other Operational Expenses	US$
		RPK	million x KM
		FRTK	million x KM
		ASK	million x KM
		FATK	million x KM
		Size of Self-Owned Fleet	n
		Flight Waypoints	n

Table 2
Cont.

Author	Type of efficiency	Variables	Measurement forms
Singh et al. (2019)	Operational cost	RPK	million x KM
		Payload	KG
		Stage Length	KM
		ASK	million x KM
		Aviation Fuel Price	USD / gallon
		Ownership	N/A
Babikian et al. (2002)	Energy	ASK	million x KM
		RPK	million x KM
		Stage Length	KM
		Energy Consumed per ASK	joules / ASK
		Energy Consumed per RPK	joules / RPK
Merkert and Hensher (2011)	Technical, allocative, and cost-efficiency	RPK	million x KM
		RTK	million x KM
		Labour	n
		ATK	million x KM
		Freight Price	USD/FTE
		ATK Price	USD/ATK
		Airline Size (ASK)	million x KM
		Aircraft Size	n
		Stage Length	KM
		Fleet Age	n
		Aircraft Families	N/A
		Aircraft Manufacturers	N/A
Barros et al. (2013)	Technical	Total Cost	log
		Number of Employees	n
		Number of Gallons	n
		Total Revenue	n
		RPM	million x KM
		PLF	percentage
Sakthidharan and Sivaraman (2018)	Technical and scale	RPKM	million x KM
		FTKM	million x KM
		ATKM	million x KM
		CASK	million x KM
		Fuel per ASK	log
		CASK ex-fuel	log
		Maintenance per ASK	log
		Ownership per ASK	log
		Employees	n

Source: research data.

5. METHODS

The conduction of a scientific study is done through a specific method or technique that refers to the best approach to answer the research questions and reach the defined objectives. Additionally, due to the different research objectives, it is necessary to classify them according to the purposes, means, and nature of the data (Davies, 2020). For the purposes of this paper, this research is classified as exploratory, descriptive, and quantitative in line with Davies (2020), Hancock et al. (2010). It is exploratory, as it seeks to better understand and identify the performance and operational efficiency indicators of airlines companies. It is also descriptive thus, it tries to describe the possible relationships between these indicators and the performance of airlines, as well as the direction and intensity of these relationships. Finally, it is quantitative because it employs a technique used to collect information of a numerical nature,which is then analyzed using statistical methods.

Due to the nature of the research questions and the type of data, panel data analysis has been used. The main objective of the regression models for panel data is to study the behavior of a certain dependent variable, which represents the phenomenon of interest, based on the behavior of explanatory variables, whose changes can occur between individuals, entities, or companies at the same moment of time (cross section), as to the length of time under the assumption that the cross-section units are independents (Washington et al., 2011).

According to Batalgi (2008), Washington et al. (2011), and Wooldridge (2002), there are several advantages to working with panel data analysis compared to using non-cross-sectional data or time series. First, as it has both a temporal and a cross-sectional dimension, these types of data provide much more information about the phenomenon under study, increasing the degrees of freedom and, consequently, the efficiency of the estimator. Second, a panel of data contains more variation and less collinearity between variables, as well as allowing the specification of more sophisticated models, incorporating more complex behavioral assumptions. Thirdly, this kind of data allows us to reduce the deleterious influence on the properties of the estimators due to the omission of specific, observable, but time-invariant relevant variables, due to lack of measures, for example.

For the purposes of data analysis in this paper, a panel data analysis has been conducted considering the following assumptions, according to Wooldridge (2002), Batalgi (2008), and Washington et al. (2011):

a. Regression considering that the intercept of the model and its angular coefficients are constant over time and space, and the error term captures the difference in time and between individuals (pooled);
b. Regression considering that the angular coefficients are constant and the intercept varies between individuals (fixed effects);

Regression considering that the intercept assumes a common mean value among individuals and the angular coefficients vary over time and among individuals (random effects).

The choice of parameters for calculating airline efficiency has been made by data availability (ANAC dataset), and by reviewing the previous studies. Data for explanatory variables come from the database from the National Civil Aviation Agency (ANAC) in Brazil. Data were collected from operating indicators (PLF, ATK, and RPK), revenue, routes, stage length, cost and expense, fuel consumption, flown hours, and aircraft. Having full data for the whole year, the criteria for the data parameter has been constructed. The airlines chosen for this study were Avianca, Azul (with operations started in December 2008), Gol, and Latam, as these are the largest Brazilian airlines in operation from 2009 to 2017. The Table 3, presented by Oliveira et al. (2021), shows the main characteristics of these companies which are directly related to this study.

To portray operating efficiency, the PLF metric was used as a representation of capacity relative to passenger traffic to determine the proportion of capacity used divided by the available capacity, as also used by Barros et al. (2013), Joo and Fowler (2014) and Choi (2017). The PLF can be obtained by dividing RPK by ASK in percentage (ANAC, 2018).

Following the approach taken by Merkert and Hensher (2011), the size of the airline is expressed in terms of available seat kilometer capacity, represented by ASK. As the purpose of the research is to analyze in terms of passengers, air cargo operations have been discarded, which is why we use ASK instead of ATK. Just as Kölker et al. (2016), and Joo and Fowler (2014), RPK is used to show airline pricing policy, which is represented by passenger volume multiplied by route distance flown. The calculation of RPK takes into account only ASKs that were flown by passengers.

Joo and Fowler (2014) identify that revenue and expense variables were significant in explaining airline efficiency scores in Asia, Europe, and North America. Thus, these variables were included in the model. Flight costs and expenses involve the cost of crewmembers, fuel, flight equipment depreciation, aircraft leasing, maintenance and insurance, airport charges, air navigation charges,

Table 3
Main characteristics of the major Brazilian airlines (2017).

Characteristic	Latam	Gol	Azul	Avianca
Revenues				
Total revenue (billion USD)	4.7	3.2	2.5	1.2
Revenue: domestic (%)	59.0	83.8	84.3	96.2
Revenue: international (%)	41.0	15.1	15.7	3.8
Costs				
Total operating costs (billion USD)	3.8	2.3	1.9	0.9
Costs: fuel (%)	28.9%	39.3%	30.3%	36.5%
Cost per available seat-kilometer (CASK) (cents USD)	5.6	4.9	7.5	6.2
Profitability				
Total operating profits (billion USD)	0.9	0.9	0.6	0.2
Gross margin (%)	18.2	27.0	24.8	19.3
Market share (RPK) (%)	32.6	36.2	17.8	12.9
Average PLF (%)	83	80	80	85
Average aircraft size (seats)	173	168	109	151
Average aircraft age (years)	9	9	5	5
Aircraft flight hours per day	11.5	9.9	10.1	11.3
Average stage length (km)	984	1,014	700	1,036
Number of served cities	43	54	101	25

Source: adapted from Oliveira et al. (2021).

overhead costs, general administrative expenses, and other operating expenses. For cost values, the price value was obtained in units of American Dollars. The variable cost and flight expense, together with the variable net operating revenue, indicate whether the operationalization of transportation is being surplus and whether the difference between them shows positive numbers.

Total offered routes indicate the amount of routes available for an airline to travel. Stage length is calculated from the time of departure to aircraft stop, calculated by block-to-block criteria, which indicates the number of the operation hours of an aircraft, as shown in Singh et al. (2019). Total fuel consumption in liters represents the total fuel spent by an airline's entire fleet.

The TOF (take-off) variable indicates the total takeoffs taken by the entire fleet of aircraft, including domestic and international flights. TFH (total flight hour), in turn, points to the total flight time, in hours, from lift-off to the landing of the aircraft. The number of aircraft in operation and the assignment of different manufacturers (Airbus or Embraer, for example) configure fleet optimization. While Gol operates a homogeneous fleet using only Boeing, the others operate with a diversified fleet of aircraft. A homogeneous fleet lowers the costs of an airline (Merkert and Hensher, 2011), as it could facilitate crew standardization, training, maintenance, purchasing, and even negotiation with manufacturers and suppliers and increases the airline's market power. It also can have an overall efficiency impact on the airline.

Using a similar approach to Pitfield et al. (2010), and Wang et al. (2014), an equation system is estimated. In terms of the panel data regression model, the PLF is used which can be inferred by accepting the assumptions that increased flight frequency due to passenger volume (RPK) and / or aircraft capacity (ASK) positively impact the operating efficiency of the airline (Barros et al., 2013).

To conduct this study, the empirical regression model is estimated, based on the Greene (2008) and Wooldridge (2002) models, according to Equation 1.

$$\begin{aligned} Yt = \alpha &+ \sum\beta 1Wit + \sum\beta 2Wjt + \sum\beta 3Wkt + \sum\beta 4Wlt + \sum\beta 5Wmt + \sum\beta 6Wnt \\ &+ \sum\beta 7Wot + \sum\beta 8Wpt + \sum\beta 9Wqt + \sum\beta 10Wrt + \sum\beta 11Wst + \varepsilon t \end{aligned} \tag{1}$$

The regression on Equation 1 has the dependent variable PLF (Yt) and the explanatory variables, which are the vectors of operating characteristics of airlines, and represents the sum (∑) of the regression coefficients of the independent variables, observed over a period *t*. Table 4 presents the variables used to compose the model for this study, with the symbology in the model and the expected sign for each variable.

The Table 4, complemented by the Table A1 on appendix, presents the variables collected in the literature and their description, as well as whether there is a positive or negative impact on efficiency, according to the literature. For the model of this study, we also insert the TOF variable, referring to aircraft takeoffs, considered necessary to identify the operational efficiency of airlines. It is noteworthy that some variables underwent logarithmic transformations. For these, the letter L will be inserted in front of the variable's acronym, for example, LRPK and LASK.

By analyzing the observations over time, the random effects method was estimated to the collected panel data. To make a more robust analysis for the study, assumption tests were performed to choose the most appropriate model. These tests serve to examine the structural stability of a regression model involving time-series data (Gujarati, 2006).

Table 4
Variables used in the study

Variable	Description	Symbol	Expected Sign	Authors
PLF	Passenger Load Factor, also called utilization rate, is the ratio between demand and supply of air transport.	**Yt**	(+)	Barros et al. (2013); Joo and Fowler (2014); Choi (2017)
RPK	Revenue Passenger Kilometers, which describes the number of seats sold on a given route, in kilometers.	**Wi**	(-)	Joo and Fowler (2014); Singh et al. (2019)
ASK	Available Seat Kilometers, identifying the total passenger capacity of an airline on a given route, in kilometers.	**Wj**	(-)	Kottas and Madas (2018)
ROL	Net Operating Flight Revenue is the income that a company receives for sales of airline tickets and other products after operating expenses are deducted.	**Wk**	(+)	Joo and Fowler (2014)
TRO	Total offered routes by airlines.	**Wl**	(+)	Yu et al. (2017)
Stage Length	Stage Length indicates the distance from takeoff to landing stage in kilometers.	**Wm**	(-)	Babikian et al. (2002); Merkert and Hensher (2011); Singh et al. (2019)
CustDesp	Flight cost and expense. Expenses are directly linked to a company's air transport operation.	**Wn**	(-)	Joo and Fowler (2014); Singh et al. (2019)
Fuel	Total fuel consumption (in liters).	**Wo**	(-)	Babikian et al. (2002); Lozano and Gutiérrez (2011); Sakthidharan and Sivaraman (2018)
TOF	Indicates the number of takeoffs per route on domestic and international flights.	**Wp**	(-)	Babikian et al. (2002)
TFH	Total hours flew by aircraft, calculated by flight time.	**Wq**	(+)	Babikian et al. (2002)
ACFT	The number of aircraft in operation. Air fleet size.	**Wr**	(-)	Kottas and Madas (2018)
FAB	Distribution of aircraft by manufacturers, such as Airbus, Boeing, and Embraer.	**Ws**	(-)	Merkert and Hensher (2011); Sakthidharan and Sivaraman (2018)

Source: Research data.

6. RESULTS

In statistical tests, if individual effects are purely uncorrelated with explanatory variables, it is appropriate to model these effects as randomly distributed among the observational units using the Random Effect approach. Thus, Table 5 presents the results of the Breusch-Pagan test based on the Lagrange multiplier (Greene, 2008; Wooldridge, 2002).

The test presented in Table 5 assumes that the variances of the error terms are constant (homoscedasticity). The test can be interpreted so that if the LRPK variable increases by 1, the other variables remain the same, and operational efficiency increases by about 1.76 on average. This same reasoning applies to all other variables.

Few variables showed a strong relationship, indicating that ordered data may present multicollinearity problems (it has an almost perfect fit $R^2 = 0.999$). According to Gujarati and Porter (2011), this sampling phenomenon of regression should not receive as much attention, as it does not omit exact non-linear relationships between variables, nor generate bad or weak estimators, nor invalidate the model.

The Breusch-Pagan test suggests the existence of random effects (Prob> $Chi^2 = 0.0000$) and, therefore, corroborates to use this model for Multiple Regression. Under the Random Effect model, it is assumed that it is possible to extrapolate the results of the regression coefficients of this sample of the population, in other words, the sample entities were considered to have been randomly selected to represent the entire (Greene, 2008; Wooldridge, 2002).

6.1. Descriptive statistics of variables

Table 6 presents a descriptive analysis of the sample of four Brazilian airlines from 2009 to 2017, including the dependent variable PLF and the other independent variables, in a total of 36 observations for each variable. It is observed that PLF presents relative variability given the minimum value of 0.63 of Gol and a maximum of 0.84 of Avianca, with an average of 0.77. This indicates that the four airlines approached have relatively similar PLF measures. The number of passengers paid, represented by the RPK, averages 27 billion and numbers ranging from 1 billion RPKs to 60 billion RPKs, with a standard deviation of 20 billion.

The number of available seats kilometers (ASK) assumes values from 2 billion ASKs per year to 76 billion, with an average of 35 billion ASKs. This variation can be explained by the start of operations of the Azul Airline in 2009, which started at that time with only 14 aircraft. Also, all airlines increased their fleets during the period covered in this study, which also reflects the numbers of other variables, such as revenue, offered routes, number of takeoffs, and total hours flown.

Net operating flight revenue (ROL) has a mean of $2.22 billion and ranges from $133,000 to $18 million, according to airline air services. Revenue growth is due to airlines being expanding and making strategic deals with other airlines, as well as extra revenues such as baggage charges and other fees. In the total number of offered routes (TRO), the average mean is 4,122, and the standard deviation of 2,339 routes.

The Stage_Length parameter indicates mean, minimum, and maximum of, respectively, 204 million, 20 million, and 401 million kilometres flown. Airlines have expanded routes to more airports, started international flights, and signing codeshare agreements with other international airlines, such as Azul, in 2015 and 2016, which partnered with United, then TAP and HNA (Azul, 2019). In its turn, Gol, in 2011 and 2014, signed codeshare agreements with Qatar Airways and a strategic partnership for flight expansion with Air France - KLM (Gol, 2019). Then Tam, in 2009, acquired Pantanal Linhas Aéreas and merged with LAN Chile, giving birth to Latam Airlines Group in 2012, adopting the trade name Latam from 2014 (Latam, 2019). Then Avianca, in 2015, joined the Star Alliance promoting codeshare expansion (Avianca, 2019).

Table 5
Random effects estimation results and Breusch-Pagan test

Number of obs: 36
Number of groups: 04
R-sq: Within = 0.9992
Between = 1.0000
Overall = 0.9994

PLF	Coef.	Std. Err	z
LRPK	1.768203***	.0256692	68.88
LASK	-1.684093***	.0161259	-104.43
LROL	-.0043833***	.0023062	-1.90
TRO	1.77e-07**	4.54e-07	0.39
Stage_Length	-.2632301***	.0565904	-4.65
LCustDesp	-.0146038	.0145112	-1.01
LFuel	.0017885	.0040727	0.44
LTOF	-.0507439**	.0202314	-2.51
LTFH	.2402087***	.0549988	4.37
ACFT	-.0000179	.0000192	-0.93
FAB	-.0000627	.0008451	-0.07
_cons	1.366688***	.1022241	13.37

Breusch – Pagan Test
$Chi^2 = 42527.74$
Prob > $Chi^2 = 0.0000$

Note: *, **, and *** indicate statistical significance at the level of 1%, 5%, and 10%, respectively.
Source: Research data.

Table 6
Descriptive statistics of the sample

Variable	Mean	Std Dev.	Min	Max
PLF	0,774468056	0,055441272	0,636194667	0,845162654
RPK	27.024.038.688	20.518.815.984	1.429.108.604	60.633.042.188
ASK	35.256.112.582	26510726104	2.008.865.973	76.700.855.192
ROL	8.492.025,56	11694737,27	376.590	71.182.091
TRO	4.122,722	2.339,04	369	8143
Stage_Length	204.598.204	126593547,8	20.251.378	401.489.433
CustDesp	6.746.135.514	4.799.928.027	490.821.693	14.962.691.500
Fuel	1.255.085.297	968610674,1	146.931.998	4.010.290.000
TOF	198.620	108715,97	23.820	316.967
TFH	364.029	208719,4979	41.247	650.794
ACFT	103,19	55,66	14	203
FAB	1,805556	0,7099072	1	3

Source: Research data.

The variable flight cost and expense have a mean of $6.74 billion, a standard deviation of $4.79 billion and a minimum of $490 million, and a maximum of $14.96 billion. This disproportionate variation is mainly due to the average price of a barrel of oil in the international market, one of the main inputs in the sector, and the high price of the dollar. The variable total fuel consumption has a mean of 1.25 billion liters and a standard deviation of 968 million liters. Year-over-year numerical growth reflects the acquisition of new aircraft in the airline fleet and the increase in routes. The number of takeoffs has a mean of 198,000, and variability ranges from almost 24,000 to 317,000.

The performance variable in terms of total hours flown has a mean of 364 thousand hours, a standard deviation of 208 thousand hours and variability from 41 thousand hours to 650 thousand flight hours. In general, it is observed that the aircrafts with larger capacity present greater utilization of hours flown per day. Another notable growth was in the number of aircraft in operation that ranged from 14 to 203 aircraft, with a mean of 103 aircraft. Finally, aircraft distribution by manufacturer varies from 1, with Gol operating only with Boeing, to 3, in which Avianca has already operated with the Airbus family (318, 319, 320), Embraer EMB-120 and Fokker-100. Azul also operates with 3 manufacturers (Embraer, Airbus, and ATR). Table 7 presents the results of the annual mean of the airline´s PFL analysed in this study.

Regarding the analysis of the annual mean of the PLF, as shown in Table 7, it is noted that Azul presents a load factor of 75% in 2009, the first year of operations and increases to 82% in 2017. Gol has mean of 72% of occupancy increasing year after year, and an increase of 16% from 2009 to 2017. Avianca follows the same line of growth of PLF, with annual mean growth of 1.67% and Latam that jumped from 68% of average occupancy in 2009 to 84%.

7. DISCUSSION

Considering the tests performed, the results pointed to the use of the Random Effects model to analyze the four Brazilian airlines. It is noteworthy that the results of the panel data model estimation are interpreted as an average response for the analyzed companies. This study aimed to investigate the relevance of operational indicators in airline's management to provide better operational efficiency. Thus, based on the regression results, it is possible to identify the coefficient of performance indicators that make up the conceptual model for this study.

Table 7

Analysis of the annual mean of the airline's PLF variable

Ano	Avianca	Azul	Gol	Latam
2009	0,7114	0,7541	0,6361	0,6812
2010	0,7394	0,792	0,6683	0,7204
2011	0,786	0,811	0,6812	0,7369
2012	0,7937	0,7924	0,6990	0,7657
2013	0,8211	0,8021	0,6991	0,7970
2014	0,8274	0,7936	0,7695	0,8285
2015	0,8338	0,7957	0,7724	0,8213
2016	0,8380	0,7974	0,7756	0,8344
2017	0,8451	0,8205	0,7975	0,8406

Source: Research data

Operating indicators have a positive or negative impact on operating efficiency. Thus, parameters with negative signals ASK, ROL, Stage Length, CustDesp, TOF, ACFT, and FAB are inversely proportional to operational efficiency, in other words, if each of these variables increases 1 and the others remain constant, the operational efficiency decreases. On the contrary, we present the variables RPK, TRO, Fuel, and TFH, which are directly proportional to the operating efficiency of airlines.

The purpose of the technique was to estimate the average variation of the effects of explanatory variables among the airlines Azul, Gol, Avianca, and Latam. The model is relatively consistent with the arguments found in the literature, so that the dependent variable is significant at 90% confidence, and most of the explanatory variables were favorable to explain the operational efficiency of airlines. From this perspective, the variables CustDesp, Fuel, ACFT, and FAB were not significant, but this does not mean that they have no effect on operational efficiency.

The PLF was used to represent the operational efficiency of the airlines addressed in this study, as the largest load factor tends to increase companies' profitability and marketshare, as well as estimating the strategic interest of the main service operations (Choi, 2017; Joo and Fowler, 2014). Barros et al. (2013) point out about PLF that the closer to number one, the operator is more technically efficient.

The variable Cost and Expense (CustDesp) showed a negative sign following Singh et al. (2019)'s model, since minimizing the operating cost would reflect lower fuel costs, for example, and would imply greater operational efficiency. According to Babikian et al. (2002), Lozano and Gutiérrez (2011), and Sakthidharan and Sivaraman (2018), an efficient fleet is one that can consume less fuel to lower operating costs. However, it is noteworthy that the cost of fuel is subject to changes in the price of a barrel of oil and fluctuations in dollars, reflecting the final operating costs. Babikian et al. (2002) demonstrate that fuel consumption is more associated with operational rather than technological factors because aircraft spend so much time on ground maneuvers and congestion.

Sakthidharan and Sivaraman (2018) state that the adoption of a fleet of aircraft with renewed technology and design contributes to lower fuel consumption, implying the effect of fuel on better operational efficiency. Previous experience, as reported by Singh et al. (2019), has shown that high fuel prices negatively affect air travel demand. Thereby, airlines will reduce fuel consumption by manipulating other services, such as reducing flight frequency, to address price and operating costs. In this sense, according to the results of this study, increasing fuel consumption implies a greater offer of routes and frequency of flights to serve more customers. In this case, although the variable Fuel is not statistically significant, it is understood that it is a key parameter to explain operational efficiency.

Taking into account the results of Kottas and Madas (2018) survey, airlines from the American continent, especially the US, have a larger fleet size than Asia, Europe, and Oceania. For this reason, they face diseconomies of scale, affecting the efficiency of scale and overall efficiency due to the economic viability and operational flexibility of these aircraft, drawing greater attention of airline executives and managers to limit airline size to achieve operational efficiency. Thus, the variable ACFT is following the literature that the smaller fleet, the more efficient the airline.

Merkert and Hensher (2011), and Sakthidharan and Sivaraman (2018) clearly show that homogeneous fleets are more efficient as they reduce crew training, maintenance, purchasing, and other costs. Even though the variable FAB used in this research did not have a significant impact on the operational efficiency of airlines, it is a considerable variable to represent the counterpoint that the smaller number of aircraft and the adoption of homogeneous fleets, about the mix of fleets of different families (e.g., B737, B737max), and manufacturers, results in greater operational efficiency, in accordance with related literature.

The other variables - RPK, ASK, ROL, TRO, Stage Length, TOF, and TFH - were significant and may explain a portion of the operational efficiency of the airlines addressed in this study. The output RPK used in the model of this study to assess airline pricing policy associated with passenger demand shows that RPK and operating efficiency are directly proportional, contrary to Joo and Fowler (2014) and Singh et al. (2019). These authors demonstrate that more costly passengers would not lead to the greater operational efficiency of the airline.

Thus, the increase in operating costs, such as fuel and maintenance, is supported by the containment of operating expenses and not by the ticket increase. On the other hand, as a result of this survey, boosting RPK could mean the increase of revenue through airline growth to meet passenger demand behavior. Thus, airline internal policies to expand the most sought destinations, including domestic and international markets, influence the increasing number of passengers carried, which increases the airline's revenue. In times of crisis, such as currency devaluation or rising oil prices, it is observed changes in flight supply, as measured by ASK, offset by the possible decrease in RPK.

As expected from the inversely proportional relationship of ASK and operating efficiency, as evidenced by Kottas and Madas (2018), the lower available seat offer per kilometer means a more efficient and profitable airline. ASK refers to the number of aircraft operated and measures the capacity and size of the company. To have a better competitive position, the limitation of passenger traffic capacity is associated with increased economies of scale and, consequently, greater operational efficiency.

The negative relationship between net operating revenue (ROL) and PLF indicates that revenue growth has negative influences on the operating efficiency of airlines, in disagreement with the results reported by Joo and Fowler (2014). This evidence reflects the competitiveness of the companies, as the increase of the ticket can have a dispersion effect of passengers, who will seek the lowest ticket price. Strategically, revenue management also indicates that the airline should grow, but size should be limited so as not to face problems of diseconomies of scale when the operating cost grows more than expected, causing losses to companies.

An increasing number of routes (TRO), called waypoints by Yu et al. (2017), leads airlines to greater operational efficiency. The more destinations an airline offers, the more convenience passengers will have, thus attracting more travellers. The greater offer of routes is also associated with the alliance network formed between the airlines that offer the largest choice of destinations. Also, routes may follow time patterns, so airlines may have more or less aircraft to serve a particular region.

Parallel to the results of this research, findings in the literature highlight the negative relationship between Stage Length and efficiency, such as the study by Babikian et al. (2002), that demonstrated that aircraft flying less than 1000 km have energy efficiency values in the order of 1.5 to 3 times larger than aircraft flying over 1000 km. Merkert and Hensher (2011) and Singh et al. (2019) highlight this same relationship by understanding that a long Stage Length can burn more fuel, including additional fuel taken on board, and increase the flight cost and operating expense. Also, delays in ground maneuvering and air traffic congestion have a negative impact on flight efficiency by burning unnecessary fuel.

In line with the studies by Babikian et al. (2002), a negative relationship was observed for the number of takeoffs per route (TOF) and positive for the total flight hours (TFH). An explanation for this condition is that before takeoff, aircraft spend time at airports performing taxiing and maneuvering at gates, and takeoff is the phase in which fuel is most burned. For the total flight hours, it is understood that the aircraft has higher energy efficiency in the cruising phase due to less fuel burn and less energy use in this flight stage, making the operation more efficient when the aircraft spends more time in flight than on the ground (Babikian et al., 2002).

8. CONCLUSIONS

The growth of the air transport sector reflects the interest of stakeholders in this means of transportation. As a result, this paper has investigated the relevance of operational indicators to provide better-operating efficiencies for airlines. Adopting strategies to increase operational efficiency makes airlines more competitive, improves passenger service, raises performance rates, and, at the same time, underpins the subsequent analysis of economic and operational indicators. Information on performance indicators that impact airlines' costs and efficiency is crucial for strategic change. It also enables companies to create guidelines for creating short, medium- and long-term strategic planning.

The methodological approach using a panel data econometric regression model for a period from 2009 to 2017, capable of enabling the estimation of the coefficients, was adequate to obtain the best fit for the assigned data. In order not to bump into the lack of data uniformity, all data were taken from reports of the Brazilian National Civil Aviation Agency (ANAC), which have a high degree of reliability due to the credibility of the source.

Under the regression model presented in this study, airlines' operational efficiency is achieved when there is a greater offer of routes and frequency of flights to meet the behavior of passenger demand, generating higher revenue passenger-kilometer. On the other hand, limiting the growth of the airline by controlling the transport capacity of aircraft indicates increased operational efficiency so that companies do not face problems of scale diseconomies, generating losses.

It was also evidenced that a shorter stage length and reduced takeoffs have an inversely proportional effect on operational efficiency, due to fuel consumption and energy efficiency issues. The total flight hour's parameter reaffirms that aircraft are more efficient in the flight phase, especially in high altitudes when in cruise, due to the lower fuel consumption in this phase, also generating greater flight autonomy. As it flies, fuel burns and consequently reduces the weight of the aircraft, gradually consuming less fuel.

Although variables such as CustDesp, Fuel, ACFT, and FAB were linked to operational efficiency, they were not significant in the panel data regression model analysis. The variables RPK, ASK, ROL, TRO, Stage_Length, TOF, and TFH comprise airline management aspects that need greater attention from airline and airport managers and executives, as they have demonstrated significance for strategic management practices for companies to obtain a better competitive position.

The scarcity of data cannot be negligible in studies related to the subject of this research, since practically all previous studies reported considerable research efforts not to be restricted in this limitation.

Despite having used a reliable database and the advantages of econometric analysis of panel data, the research is not exempt, like any other, from limitations. This is because using panel data increases the risk of having incomplete samples or data collection problems. Furthermore, a panel data may include errors resulting from the data collection, not constituting a random sample due to self-selectivity, or lack of data in successive model perform due to lack of recording of information. Regarding this research, something that to some extent may have occurred because the Brazilian air sector is concentrated, and some companies are no longer significant players in the air transport market.

Of course that, future research could investigate more extensively the operating factors that drive the increased operational efficiency of airlines, grouped in the sector or individually including new entrants, associated with aspects that portray airlines' forms of cooperation, mergers/acquisitions, the age of the adopted fleet, and airport operational aspects, such as runway size, beaconing, airport space, among others.

ANAC dataset show that the financial results (gross margin, EBIT margin, and net margin) of the four airlines analysed in this study decreased between 2009 and 2018 (ANAC, 2018). Using the strategic management literature, such as the distinction between operational efficiency and strategy (Porter, 1996), future studies could discuss the performance paradox (Chaharbaghi, 2007) and the need for business model innovation (Spieth et al., 2014) in the airline industry. Performance paradox, which manifests when a significant majority of effort leads to a minority of the results, can be explained through the decay of cause-and-effect models (Chaharbaghi, 2007) and companies should seek and consider improvements to business models at all times (Teece, 2010).

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AUTHOR'S CONTRIBUTION

AP: Research development, Data analysis and Final review; MC: Supervision, Contribution to the contextualization of the theme, Literature review and Final review; RMR: Contribution to the contextualization of the theme, Literature Review; MAS: Research Guidance and Literature Review.

CONFLICTS OF INTEREST

The Authors declare that there are no conflicts of interest in submitting this article.

APPENDIX

Table A1
Abbreviations Description

Acronyms/Abbreviations	Nomenclature / symbols
ANAC = National Civil Aviation Agency	Yt = operational efficiency
ASK = Available Seat Kilometers	α = intercept of the regression line (constant)
ATK = Available Tonne Kilometres	∑βn (n = 1,2,...,n) = sum of the coefficients of each variable (angular coefficients)
CASM = Cost per Available Seat Miles	Wzt (z = i,j,...,u) = explanatory variables: PLF (Yt), RPK (Wi), ASK (Wj), REV (Wk), TRO (Wl), *Stage Length* (Wm), CostExp (Wn), Fuel (Wo), TOF (Wp), TFH (Wq), ACFT (Wr), MAN (Ws)
CASK = Cost per ASK	
DOC = Direct Operating Cost	εt = error term (difference between the actual value of Y and the predicted value of Y through the model for each observation).
DEA = Data Envelopment Analysis	
FATK = Freight Available Tonne Kilometers	
FRTK = Freight Revenue Tonne Kilometers	
FTKM = Freight Tonne Kilometers	
ICAO = International Civil Aviation Organization	
KM = Kilometer	
LCC = Low Cost Carriers	
PLF = Passenger Load Factor	
RASM = Revenue per Available Seat Miles	
RPK = Revenue Passenger Kilometres	
RPM = Revenue Passenger Miles	
RTK = Revenue Tonne Kilometres	
TON = Tonne	