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IMPACTS OF THE COVID-19 PANDEMIC ON THE EFFICIENCY OF BRAZILIAN DOMESTIC AIR TRANSPORTATION

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Abstract: The Covid-19 pandemic has given rise to broad challenges in the air transportation sector by leading to the closure of borders and imposing restrictive measures taken immediately. At the same time, Brazil struggled to contain and better prepare to deal with the consequences of the pandemic. Given the context, this work aims to analyze the impact of Covid-19 on the efficiency of air transportation sector and evaluating the prospects of its recovery compared to the pre-pandemic level. The present study makes use of Data Envelopment Analysis methodology seeking to identify the technical efficiency of both passenger and cargo flights. The methodology was applied by adopting relevant input and output indicators. We confirmed the negative impacts on the sector suffered from the pandemic. Cargo flights in Brazilian domestic market experienced a larger loss than passenger flights. Moreover, the study shows the Brazilian market did not perform ideally to prevent impacts of the second wave of Covid-19. For governments and policy makers, they need to carefully consider the effects of policies to be implemented. Our research also provides decision-making factors to organizations and companies related to business performance.

Keywords: Air transportation, Covid-19, Recovery of market, Efficiency estimation, DEA

INTRODUCTION

The air transportation sector is a fundamental part of the Brazilian economy. There are 2,885 civil aerodromes in Brazil, in other words, the second largest number in the world following the United States (Pereira & Soares de Mello, 2020). This notable number of aerodromes reveals that, as an emerging economy, Brazil understands the pivotal role of developing the air transportation sector, and it is an essential element to support the country's ambition to expand trade and tourism. The data for 2019 disclosed by the International Air Transport Association (IATA) estimates that nearly 839,000 jobs are sustained by air transportation. Moreover, 1.1% of the GDP of the country is composed of the production of this sector and the market generated by foreign tourists arriving by air.

The air transportation sector is one of the sectors most affected by the Covid-19 pandemic in Brazil. In April 2020, nearly 80% of the fleet of the principal airline companies in the country remained grounded (Forsberg, 2020). The Covid-19 crisis brought not negligible challenges to each of these companies. As the traditional passenger segment changed its purchasing behavior, many business travelers are seeking videoconferencing instead of traveling. Suggestive evidence is found that business-oriented routes are impacted more strongly than leisure ones. An important strategy for companies to survive is to find ways to cultivate non-business passengers' demand (Santos et al., 2021). The airline companies are struggling to survive because of the steep drop in the passengers' demand and the continuation of the exorbitant cost of maintenance of aircrafts and companies' operations.

The study conducted by Hotle and Mumbower (2021) revealed that the connectivity of the air transport system was significantly affected by the pandemic. From a global perspective, the sector's recovery has been considerably slow. Most companies in the aviation market are not expected to see their growth return to pre-pandemic levels until at least 2023. Full recovery is fraught with uncertainty in the face of an ever-evolving pandemic situation. Furthermore, the losses to companies that occupy important positions in the domestic market are expected to increase even more. With the fuel price crisis caused by the pandemic in Brazil, demand for the air transportation sector is hugely impacted. According to the Brazilian Association of Airlines (ABEAR, 2021), the price of aviation kerosene (QAV) in the second quarter of 2021 registered an increase of 91.7% compared to the same period in 2020, accumulating an increase of 47.7% from January 4th to October 25th. The study of Fernandes et al. (2014) reveals that a fifty percent increase in the cost of fuel, combined with a movement of duopolization in the market, would cause losses of almost forty percent in the economic well-being of the consumer.

Due to the fluctuating situation which is difficult to predict, airline companies need to allocate their resources efficiently. If the supply of the transportation capacity exceeds the demand of the sector, undoubtedly there will be a waste of resources and damage to companies' profit. Thus, it is necessary to have instruments that allow the evaluation and optimization of the use of resources by the airline companies, so that the supply of transport capacity is at a proper level to accurately meet all the demands generated. One such tool is the Data Envelopment Analysis (DEA).

There have been extensive studies using the DEA methodology, a mature input-output research tool, to analyze airline efficiency and performance benchmarking studies (Zhu, 2011; Lin et al., 2021). To calculate the efficiency of airlines, Araujo Junior et al. (2019) use the DEA. In the analysis, 41 international airlines were selected from the markets of North and South America, Europe, and Asia.

Passenger and cargo flights have significant differences that can be studied furtherly. Most existing studies have focused on commercial flights, while some other studies find out that Covid-19's impact is much smaller on cargo than on passenger traffic (Pearce, 2020). Sun et al. (2021) summarize the study of Nhamo et al., (2020); Nižetić (2020) and Li (2020) showing that cargo flights were not significantly affected, given the need to transport medical equipment and the ambition to keep alive the exchange of crucial goods across borders. This effect was further analyzed by Bombelli (2020), who investigated the global networks of FedEx, UPS, and DHL; finding that, after small fluctuations in the early stages, these operators appear to have unaffectedly survived the pandemic.

Given the unpredictable nature of the virus and its impact on the economy, there is a need to continually track and evaluate the effects of this pandemic on the transport sector in order to provide the necessary reflections for policymakers and the economy. The present study makes use of the DEA methodology seeking to identify the technical efficiency of both passenger and cargo flights. The methodology was applied by adopting relevant input and output indicators.

The next section includes the theoretical background, with a description of the Data Envelopment Analysis (DEA); presents the methodological procedures used in the study. The third section shows the steps from data selection to the analysis of the results, highlighting the efficient Decision Making Units (DMUs) in the study, difference among five geographic regions, as well as comparison between Brazil and USA markets. Finally, we present the study's discussions and conclusions, including limitations and suggestions for future work.

METHODOLOGY

The Data Envelopment Analysis (DEA) was first proposed by Charnes, Cooper, and Rhodes (1978) in their work "Measuring the efficiency of decision making units". This can be called as CCR-DEA model. The tool estimates an efficiency frontier that determines the productivity-limiting points at which a

Decision Making Unit (DMU) is considered relatively technically efficient. The technical efficiency of other DMUs is calculated by the distance of these points to the estimated frontier. The efficiency of a DMU decreases as it locates farther from the efficiency frontier.

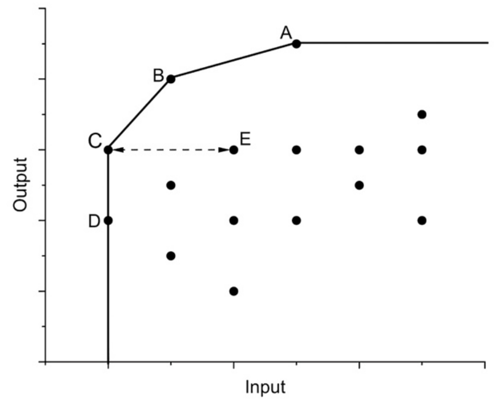


Figure 1: DEA General Concept

Figure 1 illustrates the overall concept of the DEA. The methodology selects the most efficient DMUs and draws a convex efficiency frontier using these points. The points *A*, *B* and *C* are considered efficient DMUs because they situate on the frontier. On the contrary, point *E* is inefficient because, technically speaking, it can operate on point *C* which uses fewer inputs to produce the same quantity of outputs. The inefficiency is measured by a function of the distance between *C* and *E*. The point *D* represents the concept of slack or excess of inputs. Its location on the frontier doesn't mean efficiency, but the excess utilization of inputs. This problem is caused by the non-imposition of a functional form (Postali, 2016).

The widely applied input-orientated CCR-DEA model can be defined as follows: consider that there are *I* DMUs. Every DMU uses *N* inputs to produce *M* outputs. DEA introduces a measure of efficiency by finding the optimal weights of a weighted ratio of all outputs to all inputs. The problem can be represented by:

$$\max_{u,v}(u'q_i/v'x_i) \quad (1)$$

subject to

$$u'q_j/v'x_j \leq 1, j = 1,2,\dots,I \quad (2)$$

$$u,v \geq 0 \quad (3)$$

$$v'x_i = 1 \quad (4)$$

where x_i is an *N X 1* vector of all the inputs the DMU *i* used, q_i is an *M X 1* vector of all the outputs the DMU *i* produced, *u* is an *M X 1* vector of output weights and *v* is an *N X 1* vector of input weights (Coelli et al., 2005, p. 162-163).

This process has the purpose of finding values of *u* and *v*, so that the efficiency measure is maximized for the *i*-th firm. Equation (2) represents the constraint that the measure of the efficiency of any DMU should be less than or equal to 1; constraint (3) states that the values of *u* and *v* should not be negative; constraint (4) is used to avoid an infinite number of solutions.

Moreover, the above formulation can be reformed by using the duality in linear programming to equivalent one (Coelli et al., 2005, p. 163):

$$min_{\theta,\mu}\,\theta \quad (5)$$

subject to

$$-q_i + Q\mu \geq 0 \quad (6)$$

$$\theta x_i - X\mu \geq 0 \quad (7)$$

$$\mu \geq 0 \quad (8)$$

where θ is a scalar, μ is an *I X1* vector, *Q* is an *M X I* matrix that groups in its columns the outputs produced by each DMU, and *X* is an *N X 1* matrix which groups in its columns the inputs used by each DMU (Freitas, 2013). We can solve the linear programming problem for

I times to receive the value of θ for each DMU.

The CCR model defined in (5) – (8) seeks to assess total efficiency, identify efficient and inefficient DMUs, as well as determine how far from the efficiency frontier the inefficient units are. However, in this model, the efficiency frontier indicates that DMUs are operating at optimal scale, in other words, constant returns to scale (CRS), which is not practical at all times due to the existence of imperfect competition, government regulations, constraints on finance, etc. In addition, the scale efficiency (SE) is confounded with the technical efficiency (TE) when the scale is not optimal (Worthington & Dollery, 2000). The problem can be solved by adding a restriction of convexity $I1'\mu = 1$ to the formulation, the model will become as follows:

$$min_{\theta,\,\mu}\,\theta \qquad (9)$$

subject to

$$-q_i + Q\mu \geq 0 \qquad (10)$$

$$\theta x_i - X\mu \geq 0 \qquad (11)$$

$$\mu \geq 0 \qquad (12)$$

$$I1'\mu = 1 \qquad (13)$$

where $I1'$ is an *I X 1* vector of ones.

The purpose of equation (13) is to guarantee that the comparison only happens between DMUs of similar sizes, which is ignored in the CCR model (Postali, 2016).

The input-orientated BCC model defined in (9) – (13) considers the existence of variable returns to scale (VRS) at the efficiency frontier (Banker, Charnes & Cooper, 1984). $0 \leq \theta \leq 1$ obtained from the formulation is the score of efficiency of each DMU. $\theta = 1$ means that the DMU is located on the efficiency frontier, which means it is an efficient DMU. Those DMUs with a score less than 1 can decrease their inputs consumed for giving outputs, thus, they are considered inefficient.

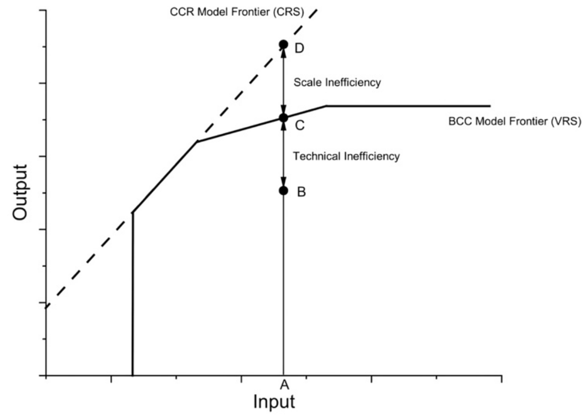


Figure 2: CCR and BCC Models

Figure 2 shows the efficiency frontiers of the CCR and BCC models.

We can get scale efficiency by running both CRS and VRS models. The CRS technical efficiency measure can be decomposed into pure technical efficiency and scale efficiency. The concepts are illustrated in ratio as follows:

$$TE_{CRS} = AB/AD \qquad (14)$$

$$TE_{VRS} = AB/AC \qquad (15)$$

$$SE = AC/AD \qquad (16)$$

where all the measures vary in the interval (0,1].

From the equations above, we can derive that:

$$SE = TE_{CRS}/TE_{VRS} \qquad (17)$$

INPUTS, OUTPUTS AND DATA

The database used in this article is the passenger and cargo-only flights that happened in the Brazilian territory retrieved from the National Civil Aviation Agency of Brazil (ANAC). Information on the number of passengers, cargo and mail carried, distance flown, and fuel consumed, among others, by flight stage and by airline, is included in the database. Data are provided to ANAC on a monthly basis, until the 10th day of the following month after the reference month, by Brazilian and foreign companies operating regular and non-regular public air transport services in Brazil. Furthermore, to estimate the impact of the Covid-19 pandemic and the response of the corresponding sector, we firstly focus our data on the period of Nov. 2016 to Nov. 2021. 122 DMUs are formed by passenger flights and cargo flights and their respective data each month in this first step.

Comparing Brazil with another country can provide us with a global view to better understand how Brazil is dealing with the pandemic. In this sense, the United States was selected, as it is a world reference. To make an international scope of comparison, the same steps are applied to the data of the USA retrieved from the Bureau of Transportation Statistics (DOT/BTS). 61 DMUs are formed by scheduled passenger flights and their respective data each month.

More detailed area divisions and longer periods can provide more information. To do so, according to the Brazilian Institute of Geography and Statistics (IBGE), we divide the Brazilian territory into 5 geographic regions considering geographic, social and economic factors (IBGE, 2017). In addition, we expand our data to the period from Nov. 2016 to Oct. 2021. Flights from one region to another in each month are considered as a DMU, a total of 2719 DMUs are formed by passenger flights and cargo flights in this second step.

It is important to carefully select variables to address indicators that represent the sector. These variables must represent a relationship between the inputs consumed and the outputs obtained through the production process, resulting in different scores of efficiencies each month.

As for input variables, we take into consideration Available Seats Kilometer (ASK), Available Tonne Kilometer (ATK), and fuel consumed for each DMU. As for output variables, we choose Revenue Tonne Kilometer (RTK) and Revenue Passenger Kilometer (RPK). Fuel consumption is considered relevant to efficiency improvements in technology and operating costs in the air transportation sector (Morrel, 2009). The unit of fuel consumption in Brazil is liter. In the data of the USA, equivalent variables are in the unit of mile and gallon. According to ANAC, ASK and ATK are important indicators of the sector's supply, while RTK and RPK represent the market's demand.

One characteristic of cargo flights is that their ASK and RPK are all zero. We use this feature to separate them from passenger flights. These two variables are ignored when calculating the efficiencies of corresponding flights. Thus, we have two groups of DMUs, one contains passenger flights, and another one is composed of cargo flights. With different sets of inputs and outputs, the efficiencies retrieved can only be compared within the same group.

Table 1: Variables used in the DEA calculation

Table 2: Descriptive statistics of input and output variables

RESULTS

Table 3 presents the efficiency scores of CCR and BCC models for passenger and cargo flights respectively for a part of the period in Brazil.

Table 3 shows that in March 2020, the efficiency of passenger flights declined to lower levels since 2016/11, and the lowest efficiency for passenger flights is in 2021/3. The results basically fluctuated around the mean, but the efficiency in 2020/3, 2021/2, and 2021/3 are relatively low. Table 3 also shows that in December 2020, the efficiency for cargo flights declined to lower levels since

2019/9, and afterwards, the efficiency had a steady increase for months. It then fluctuated and reached the lowest efficiency of 0.804 in 2021/10. Since 2020/11, the efficiency of cargo flights is relatively low, and those from 2020/11 to 2021/10 are lower than 0.9, except for April 2021. Although the efficiency started to show a tendency of increasing, it did not reach the average of these data until 2021/11.

Figure 3 presents the efficiency scores for passenger and cargo flights in the period from Nov. 2016 to Nov. 2021 in Brazil.

Scale efficiencies are calculated as CCR efficiency divided by BCC efficiency. If the ratio is equal to one, the DMU operates at constant returns to scale. The indicators of returns-to-scale (RTS) give us more details about scale efficiencies. Among 9 efficient passenger flights DMUs, 3 operate at increasing returns to scale (IRS), 5 of them operate at constant returns to scale (CRS), and only 1 of them operates at decreasing returns to scale (DRS). Among 8 efficient cargo flights DMUs, 5 of them operate at increasing returns to scale (IRS), 2 of them operate at constant returns to scale (CRS), and only 1 DMU operates at decreasing returns to scale (DRS).

Figure 4 presents the efficiency scores for passenger flights in the period from Nov. 2016 to Nov. 2021 in Brazil and the USA. According to Figure 4, we find out the efficiency score of Brazil and the USA shows an opposite tendency before the pandemic. In Brazil, low points of efficiency occur in May for 3 consecutive years since 2017, however, the score is the lowest every year in January in the USA. This finding proves the existence of different seasonality in both markets.

In March 2020, the efficiency of passenger flights declined to the lowest levels since 2016/11. The results show a larger fluctuation than Brazil. The efficiency in 2020/3, 2020/7, and 2020/8 are relatively low. We also find that the average efficiency score of the USA was lower in the pandemic than in Brazil, with an average score of 0.893, compared to 0.961 in Brazil. It is noticeable that the scale efficiency of April 2020 is only 0.186, with a small increase in the following two months. It means that the carriers reduced significantly their scale efficiency.

In February of 2020, both markets registered a drop which deteriorated in March. Then the efficiency of both markets recovered from April to June until it dropped again. From February 2020 to November 2021, the average of efficiency score of the Brazilian market is 0.961, while the USA market is 0.881. In March of 2021, the score dropped to a lower level than the anterior year in Brazil, however, this didn't happen in the USA.

The following results are obtained with the division of regions inside Brazil.

Table 4 presents descriptive statistics of the efficiency scores of CCR and BCC models for passenger and cargo-only flights respectively. Among the 1395 DMUs of passenger flights, 36 are technically efficient, in other words, with a score of 1. That is, 2.58% of the total observations. Among the 1324 DMUs of cargo flights, 13 are technically efficient. That is, 0.98% of the total observations.

By analyzing the distribution of efficiency scores calculated by the DEA, we find that the distribution of technical efficiency scores of passenger flights is negative skew, which confirms the large concentration of efficient DMUs. The result for cargo flights shows a significant difference. The distribution of technical efficiency scores of cargo flights is positive skew, which confirms the large concentration of inefficient DMUs.

Table 5 presents average efficiency scores by regions from Nov. 2019 to Oct. 2021 for passenger and cargo flights. We can find from the results that the route from North to Southeast is the most efficient for both passenger and cargo flights. Some routes

Variable	Description	Source
Outputs		
RTK/RTM	The revenue load in tonnes multiplied by the distance flown. (Passenger and Cargo)	ANAC (2021) & BTS (2022b)
RPK/RPM	The number of revenue passengers carried multiplied by the distance flown. (Passenger)	
Inputs		
ATK/ATM	The number of tonnes of capacity available for the carriage of revenue load multiplied by the distance flown. (Passenger and Cargo)	ANAC (2021) & BTS (2022a, 2022b)
ASK/ASM	The number of seats available for sale multiplied by the distance flown. (Passenger)	
Fuel Consumed	Total fuels, in liters/million gallons, used for aircraft propulsion. (Passenger and Cargo)	

Table 1 summarizes the variables used in the calculation of efficiencies.

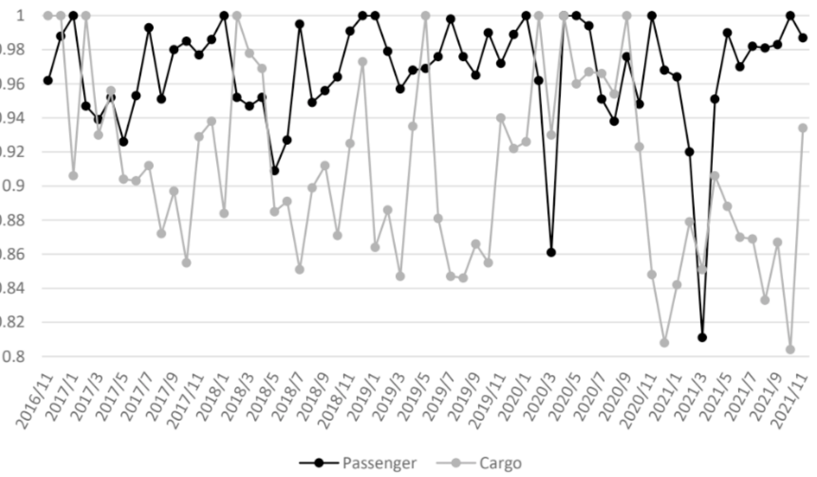
	Variable	Mean	Standard Deviation	Min	Max
Passenger Flights - Brazil	RTK	596537409.59	191988612.37	51685966	846611105
	RPK	6723624367.85	2212181008.66	506570717	9858085641
	ATK	905351313.93	275286286.49	92460453	1243101762
	ASK	8277273876.69	2586129848.91	773736445	11544616341
	Fuel Consumed	242159042.03	77977397.13	21415718	337674764
Cargo Flights - Brazil	RTK	19082532.51	3263261.42	11445022	26782205
	ATK	34028598.03	4418407.31	23873949	43389986
	Fuel Consumed	8165779.77	1028849.25	5139118	10079891
Passenger Flights - USA	RTM	5193147.82	1724580.44	312096	7260458
	RPM	50721763.23	17067479.96	2583218	71420565
	ATM	8267368.31	1938339.65	2217310	10772777
	ASM	63649460.05	14808571.64	17443924	80444128
	Fuel Consumed	904.49	193.74	330.90	1127.30

Table 2 presents descriptive statistics of input and output variables in the period of Nov. 2016 to Nov. 2021.

	Y/M	CCR	BCC	Scale Efficiency	Return to Scale
Passenger Flights	2019/9	0.960	0.965	0.995	IRS
	2019/10	0.986	0.990	0.997	IRS
	2019/11	0.968	0.972	0.996	IRS
	2019/12	0.988	0.989	0.999	IRS
	2020/1	1.000	1.000	1.000	CRS
	2020/2	0.959	0.962	0.997	IRS
	2020/3	0.850	0.861	0.987	IRS
	2020/4	0.890	1.000	0.890	IRS
	2020/5	0.995	1.000	0.995	IRS
	2020/6	0.990	0.994	0.997	IRS
	2020/7	0.949	0.951	0.998	IRS

	2020/8	0.937	0.938	0.999	IRS
	2020/9	0.975	0.976	0.999	IRS
	2020/10	0.940	0.948	0.992	IRS
	2020/11	0.994	1.000	0.994	IRS
	2020/12	0.965	0.968	0.997	IRS
	2021/1	0.960	0.964	0.996	IRS
	2021/2	0.912	0.920	0.991	IRS
	2021/3	0.806	0.811	0.994	IRS
	2021/4	0.948	0.951	0.998	IRS
	2021/5	0.978	0.990	0.988	IRS
	2021/6	0.963	0.970	0.993	IRS
	2021/7	0.979	0.982	0.996	IRS
	Average	0.952	0.961	0.991	
Cargo Flights	2019/9	0.798	0.866	0.921	IRS
	2019/10	0.854	0.855	0.999	IRS
	2019/11	0.930	0.940	0.989	IRS
	2019/12	0.878	0.922	0.952	IRS
	2020/1	0.859	0.926	0.928	IRS
	2020/2	0.891	1.000	0.891	IRS
	2020/3	0.846	0.930	0.910	IRS
	2020/4	0.831	1.000	0.831	IRS
	2020/5	0.912	0.960	0.950	IRS
	2020/6	0.914	0.967	0.946	IRS
	2020/7	0.906	0.966	0.937	IRS
	2020/8	0.856	0.954	0.897	IRS
	2020/9	0.730	1.000	0.730	IRS
	2020/10	0.801	0.923	0.868	IRS
	2020/11	0.751	0.848	0.885	IRS
	2020/12	0.750	0.808	0.929	IRS
	2021/1	0.751	0.842	0.892	IRS
	2021/2	0.762	0.879	0.868	IRS
	2021/3	0.800	0.851	0.939	IRS
	2021/4	0.814	0.906	0.898	IRS
	2021/5	0.830	0.888	0.934	IRS
	2021/6	0.815	0.870	0.938	IRS
	2021/7	0.821	0.869	0.945	IRS
	Average	0.830	0.912	0.912	

Table 3: Estimated efficiency scores for DMUs - Brazil



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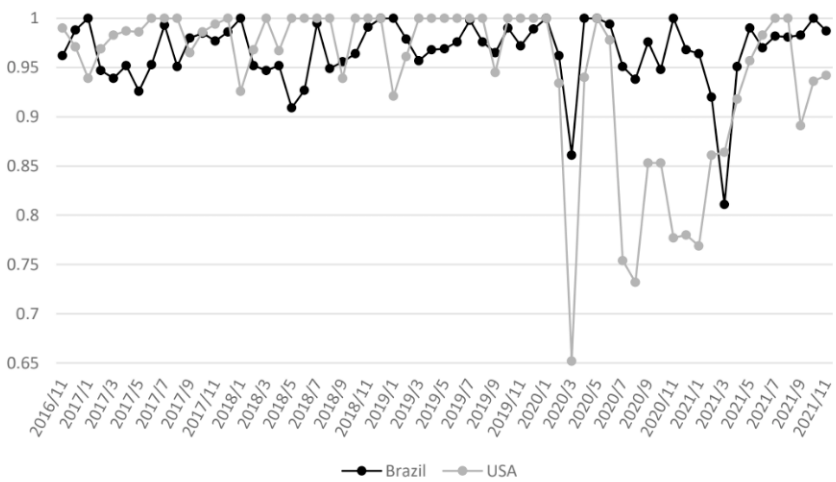

Figure 4: Estimated efficiency scores for DMUs – Passenger – Brazil and USA

		Mean	1st Quartile	Median	3rd Quartile	Standard Deviation	Minimum	Maximum	Observa-tions
Passenger Flights	CCR	0.828	0.800	0.841	0.883	0.096	0.126	1.000	1395
	BCC	0.868	0.842	0.881	0.922	0.092	0.336	1.000	
	Scale Efficiency	0.952	0.944	0.957	0.969	0.038	0.210	1.000	
Cargo Flights	CCR	0.362	0.175	0.341	0.521	0.271	0.000	1.000	1324
	BCC	0.398	0.227	0.358	0.536	0.266	0.005	1.000	
	Scale Efficiency	0.785	0.914	0.993	0.999	0.389	0.000	1.000	

Table 4: Efficiency scores by regions - descriptive statistics

	Destination	Origin				
		North	Northeast	Central-West	Southeast	South
Passenger Flights	North	0.939	0.956	0.943	0.966	0.843
	Northeast	0.966	0.953	0.965	0.957	0.950
	Central-West	0.951	0.966	0.930	0.947	0.967
	Southeast	0.971	0.968	0.950	0.943	0.955
	South	0.933	0.949	0.962	0.953	0.929
Cargo Flights	North	0.522	0.767	0.603	0.871	0.130
	Northeast	0.388	0.378	0.261	0.499	0.157
	Central-West	0.397	0.148	0.203	0.499	0.249
	Southeast	0.876	0.254	0.326	0.346	0.321
	South	0.299	0.036	0.125	0.418	0.326

Table 5: Average efficiency scores by regions

are efficient by measuring passenger flights, however, inefficient in the aspect of cargo flights, such as those from Northeast to Central-West or Southeast.

DISCUSSION

Pereira and Soares de Mello (2021) studied the efficiency of passenger flights from 2019/1 to 2020/3, and found that the lowest efficiency occurred in 2020/3, when COVID-19 was considered a global outbreak. The result of our findings is similar. We found that the tendency of passenger and cargo flights are different which is compatible with the presumption. However, in our study, the average score for cargo flights is lower, contradicting the conclusion of Pearce (2020) and Bombelli (2020) for international markets. According to IATA (2022), which represents 290 of the world's airlines, airlines transport more than 52 million metric tons of products per year, accounting for more than 35% of global trade in terms of value but less than 1% in terms of volume. Air transport is commonly employed for high-value commodities on a global scale. With fewer distance restrictions in Brazilian domestic markets, however, the need for air transportation becomes less pressing. The choice of substitute transport leads to higher elasticity of demand, thus decreasing the efficiency of the air transport sector in the pandemics when prices increase.

The air transportation sector has been affected in both Brazil and the USA. Nonetheless, the size of impact was different in the two countries. We found that the efficiency of the USA carriers was lower during the pandemic than Brazil carriers. USA carriers suffered a severe scale efficiency change in April 2020, while this effect in Brazil was milder. In the case of the USA, the Department of Transportation (DOT) issued the Final Order 2020-4-2 on April 7th, 2020 which requires that air carriers receiving financial assistance under the Coronavirus Aid, Recovery, and Economic Security Act (the CARES Act) maintain minimum air services on a nationwide basis, with some exceptions (DOT, 2020). Due to the policy, 10 marketing network carriers operated 194,390 domestic flights in April 2020 down from 701,278 scheduled flights in the previous month, a reduction of 72.28% (BTS, 2020). In Brazil, the National Civil Aviation Agency (ANAC) adopted a flexibilization measure (waiver) for the cancellation of slots from the calculation of the regularity index for obtaining historical rights by airlines. The emergency air network is 91.61% smaller than originally planned by the companies for the period. Considering the schedule of Gol, Azul and Latam, the three biggest airlines in Brazil, the drop is 56.06% of the locations served, from 106 to 46. The number of weekly flights went from 14,781 to 1,241 (ANAC, 2020). Brazilian carriers made a larger network cut than the USA due to a more flexible policy and less financial support. In our thoughts, policymakers need to carefully consider the policies to be implemented and be aware of their effects. Most governments place a high value on preserving air transportation connections in order to protect economic activity and jobs in aviation and allied industries such as tourism (Abate et al., 2020). Thus, the trade-off between connectivity and efficiency has to be taken into consideration.

As two large heterogeneous countries which globally lead the number of COVID-19 related deaths, both Brazil and the USA experience a mix between the first wave and a second wave at the beginning of 2021 (Diaz & Vergara, 2021). In Brazil, the efficiency score registered the lowest in March of 2021, one year after the pandemic started. Nevertheless, the lowest score in the USA only occurred in March of 2020, when the pandemic just started. Even though Brazil experienced a more severe second wave of the COVID-19 pandemic than other countries throughout the world (Zeiser et al., 2022), this finding shows the limited ability to predict the market's demand and the lack of preparation of the Brazilian carriers in front of the second wave of the Covid-19 pandemic.

Our finding also reveals the seasonality of passenger flights in both Brazil and the USA markets. In Brazil, the lowest efficiency occurs in May for 3 consecutive years since 2017. Meanwhile, the same situation happens in January in the USA market. This result indicates that carriers in both markets should make better adjustments to their supply in the respective month to achieve better operational outcomes and higher efficiency.

The efficiency score for passenger flights registered two minimums in 2020/3 and 2021/3. In our thoughts, the first low point is correlated to the beginning of the first wave of the COVID-19 pandemics in the eighth week of 2020. The tenth week in 2021 which belongs to March is considered the most severe moment of the second wave (Bastos et al., 2021). Further study can be conducted to find the possible correlation between the efficiency score and the evolution of pandemics. If any correlation is confirmed, the sector will have the reference to optimize its performance using the prediction of the trajectory of the pandemics.

CONCLUSIONS

The present study aims to investigate the impacts of the Covid-19 pandemics on the Brazilian domestic air transportation sector. By applying Data Envelopment Analysis (DEA) method to monthly air traffic data from Brazil and the United States, we confirm the negative impacts the sector suffered from the pandemic. Unlike in the international market, where cargo flights lost less efficiency than passenger flights due to high-value goods demand, cargo flights in the Brazilian domestic market experienced a larger loss. By comparing Brazil and the USA commercial flights market, we find out that Brazil had a better performance in March 2020, in other words, at the beginning of the pandemic, by cutting a larger number of flights. However, in March 2021, the Brazilian market didn't have an ideal performance in front of the second wave, and thus registered the lowest point. The study also calculates the efficiency of routes among Brazilian five regions. Route from North to Southeast is the most efficient, evaluated by both passenger and cargo flights. Some routes have high scores in passenger flights but need to be improved for cargo flights.

A limitation of this study is the number of indicators which is relatively narrow in scope. The findings of Kiraci et al. (2022) indicate that financial factors are important criteria to maximize the resilience needed for the survival of airline companies in crisis periods such as COVID-19. In the analysis of Zhu (2011), financial aspects such as salaries and fuel expenses per available seat mile were included. Pereira and Soares de Mello (2021) suggested using financial aspects since the occupation rate changes with the aircraft's size. This would be a beneficial improvement for further work.

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REFERENCES

Abate, M., Christidis, P., & Purwanto, A. J. (2020). Government support to airlines in the aftermath of the COVID-19 pandemic. *Journal of Air Transport Management*, *89*, 101931. doi: 10.1016/j.jairtraman.2020.101931

ABEAR. (2021). Preço do querosene de aviação (QAV) sobe mais do que gasolina e gás de cozinha em 2021. (2021). Retrieved 7 January 2022, from https://www.abear.com.br/imprensa/agencia-abear/noticias/abear-preco-do-querosene-de-aviacao-qav-sobe-mais-do-que-gasolina-e-gas-de-cozinha-em-2021-2/

ANAC. (2020). Malha aérea essencial começa no sábado. Retrieved 21 May 2022, from https://www.gov.br/anac/pt-br/noticias/2020/malha-aerea-essencial-comeca-no-sabado-28

ANAC. (2021). Dados Estatísticos. Retrieved 2 September 2021, from https://www.gov.br/anac/pt-br/assuntos/dados-e-estatisticas/dados-estatisticos

Araujo Junior, A., Souza Sampaio, N., Barros, J., Fonseca, B., & Gloria Almeida, M. (2019). Relative Efficiency of International Airlines. In *International Conference on Industrial Engineering and Operations Management*. Pilsen.

Banker, R., Charnes, A., & Cooper, W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078-1092. doi: 10.1287/mnsc.30.9.1078

Bastos, L., Ranzani, O., Souza, T., Hamacher, S., & Bozza, F. (2021). COVID-19 hospital admissions: Brazil's first and second waves compared. *The Lancet Respiratory Medicine*, *9*(8), e82-e83. doi: 10.1016/s2213-2600(21)00287-3

Bombelli, A. (2020). Integrators' global networks: A topology analysis with insights into the effect of the COVID-19 pandemic. *Journal Of Transport Geography*, *87*, 102815. doi: 10.1016/j.jtrangeo.2020.102815

BTS. (2020). Air Travel Consumer Report: April 2020 Numbers. Retrieved 22 May 2022, from https://www.bts.gov/newsroom/air-travel-consumer-report-april-2020-numbers

BTS. (2022a). Airline Fuel Cost and Consumption (U.S. Carriers - All). Retrieved 19 May 2022, from https://www.transtats.bts.gov/fuel.asp

BTS. (2022b). U.S. Air Carrier Traffic Statistics. Retrieved 19 May 2022, from https://www.transtats.bts.gov/traffic/

Charnes, A., Cooper, W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European Journal Of Operational Research*, *2*(6), 429-444. doi: 10.1016/0377-2217(78)90138-8

Coelli, T., Battese, G., O'Donnell, C., & Prasada Rao, D. (2005). *An Introduction to Efficiency and Productivity Analysis* (2nd ed., pp. 162-163). Boston, MA: Springer Science+Business Media, Inc.

Diaz, R. S., & Vergara, T. R. C. (2021). The COVID-19 second wave: A perspective to be explored. *Brazilian Journal of Infectious Diseases*, *25*(1), 101537. doi: 10.1016/j.bjid.2020.101537

DOT. (2020). Order 2020-4-2. Washington, D.C.

Fernandes, H. F., Alves, C. J. P., & Oliveira, A. V. M. de. (2014). Estudo dos efeitos de aumentos no custo do combustível na demanda por transporte aéreo doméstico. *TRANSPORTES*, *22*(3), 64–75.

Forsberg, D. (2020). COVID-19: The impact on commercial airline fleets. Retrieved 14 September 2021, from https://www.pwc.ie/issues/covid-19/impact-on-commercial-airline-fleets.html

Freitas, A. (2013). Oil windfalls and municipal social indicators: an analysis of relative efficiency. *Master's Dissertation, Faculdade De Economia, Administração E Contabilidade, University Of São Paulo, São Paulo*. doi: 10.11606/d.12.2013.tde-26032014-162649

Hotle, S., & Mumbower, S. (2021). The impact of COVID-19 on domestic U.S. air travel operations and commercial airport service. *Transportation Research Interdisciplinary Perspectives*, *9*, 100277. doi: 10.1016/j.trip.2020.100277

IATA. (2019). The Value of Air Transport in Brazil. Retrieved 27 September 2021, from https://www.iata.org/contentassets/bc041f5b6b96476a80db109f220f8904/brazil-the-value-of-air-transport.pdf

IATA. (2022). Cargo. Retrieved 16 August 2022, from https://www.iata.org/cargo/

IBGE. (2017). *Divisão regional do Brasil em regiões geográficas imediatas e regiões geográficas intermediárias, 2017*. Rio de Janeiro.

Kiraci, K., Tanriverdi, G., & Akan, E. (2022). Analysis of Factors Affecting the Sustainable Success of Airlines During the COVID-19 Pandemic. *Transportation Research Record*, 036119812211044. doi: 10.1177/03611981221104462

Lin, Y., Chang, W., Anupong, W., & Long, B. (2021). The Performance Analysis of Beibu Gulf airlines Based on DEA Model during the Pre-COVID-19 Pandemic Period. *CONVERTER*, *2021*(5), 230-235. doi: 10.17762/converter.284

Morrell, P. (2009). The potential for European aviation CO2 emissions reduction through the use of larger jet aircraft. *Journal Of Air Transport Management*, *15*(4), 151-157. doi: 10.1016/j.jairtraman.2008.09.021

Nhamo, G., Dube, K., & Chikodzi, D. (2020). Impact of COVID-19 on the Global Network of Airports. *Counting The Cost Of COVID-19 On The Global Tourism Industry*, 109-133. doi: 10.1007/978-3-030-56231-1_5

Nižetić, S. (2020). Impact of coronavirus (COVID-19) pandemic on air transport mobility, energy, and environment: A case study. *International Journal Of Energy Research*, *44*(13), 10953-10961. doi: 10.1002/er.5706

Pearce, B. (2020). COVID-19 Impact on air cargo. *4th GARS Online Panel Discussion "Covid-19 and Trade War: Boom or Bust Situation for Air Cargo?"*.

Pereira, D., & Soares de Mello, J. (2021). Efficiency evaluation of Brazilian airlines operations considering the Covid-19 outbreak. *Journal Of Air Transport Management*, *91*, 101976. doi: 10.1016/j.jairtraman.2020.101976

Postali, F. (2016). Oil windfalls and X-inefficiency: evidence from Brazil. *Journal Of Economic Studies*, *43*(5), 699-718. doi: 10.1108/jes-02-2014-0036

Santos, L. J., Oliveira, A. V., & Aldrighi, D. M. (2021). Testing the differentiated impact of the COVID-19 pandemic on air travel demand considering social inclusion. *Journal of Air Transport Management*, *94*, 102082.

Sun, X., Wandelt, S., & Zhang, A. (2020). How did COVID-19 impact air transportation? A first peek through the lens of complex networks. *Journal Of Air Transport Management*, *89*, 101928. doi: 10.1016/j.jairtraman.2020.101928

Sun, X., Wandelt, S., Zheng, C., & Zhang, A. (2021). COVID-19 pandemic and air transportation: Successfully navigating the paper hurricane. *Journal Of Air Transport Management*, *94*, 102062. doi: 10.1016/j.jairtraman.2021.102062

Worthington, A., & Dollery, B. (2000). An empirical survey of frontier efficiency measurement techniques in local government. *Local Government Studies*, *26*(2), 23-52. doi: 10.1080/03003930008433988

Zeiser, F. A., Donida, B., da Costa, C. A., de Oliveira Ramos, G., Scherer, J. N., Barcellos, N. T., ... & Rigo, S. J. (2022). First and second COVID-19 waves in Brazil: A cross-sectional study of patients' characteristics related to hospitalization and in-hospital mortality. *The Lancet Regional Health-Americas*, *6*, 100107. doi: 10.1016/j.lana.2021.100107

Zhu, J. (2011). Airlines Performance via Two-Stage Network DEA Approach. *Journal Of CENTRUM Cathedra: The Business And Economics Research Journal*, *4*(2), 260-269. doi: 10.7835/jcc-berj-2011-0063