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Submitted 07.04.2017. Approved 05.03.2018.

Evaluated by double blind review process.
Scientific Editors: José Barros Neto.

DOI: http://dx.doi/10.12660/joscmv11n1p26-36

AIRPORT ECONOMIC EFFICIENT FRONTIER

ABSTRACT

Studies about airport operational efficiency models generally disregard the correlation between operational efficiencies and economic drivers. The goal of this study is, firstly, to isolate and detail the key economic drivers and then find their efficient frontier. The methodology employed was Data Envelopment Analysis (DEA) as a non-parametric and linear programming model. It provides relative measures of efficiency using multiple inputs and outputs for a given Decision-Making Unit (DMU) without requiring a prior production function. The number of variables in this study was limited in function of the DMUs analyzed, which consisted of the following Brazilian airports: Congonhas Airport (CGH), Guarulhos International Airport (GRU) and Viracopos International Airport (VCP). Two of the airports, GRU and VCP, were found to be efficient considering this study's combination of very limited variables, meaning that theses airports, from this isolated standpoint, are maximizing their commercial, passenger parking and marketing revenues, given their terminal area and the number of yearly passengers.

KEYWORDS | Airport planning, Brazilian airports, competitiveness, decision making unit, operational.

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INTRODUCTION

Although various studies have examined airport operational performance or efficiency, fewer authors have focused on determining an efficient frontier that combined operational efficiencies and economic drivers. For these reasons, the present study aims to isolate and detail the key airports economic drivers and then find their efficient frontier, as well as their operational efficient frontier. It is expected that this study will provide a basis for a comprehensive analysis of airport economic value drivers. It complements previous research focusing on operational efficiency and aspects related to broad economic efficiency measuring, such as total airport revenues and costs.

Rather than absolute figures, financial ratios such as Return on Assets and EBITDA Margins can be a natural solution to the problems of limited number of airports in the sample and their significant differences in terms of physical and economic dimensions and operation profiles. In this respect, Brazilian airports were analyzed (Fernandes, Pacheco and Braga, 2014) concerning a broad measure of profitability against their number passengers and the potential of their cities.

Fasone, Maggiore and Scuderi (2014), for instance, analyzed the ownership structure of 25 Italian airports against key financial ratios such as return on equity (ROE), return on investment (ROI), return on sales (ROS), asset turnover (AT), equity on debts (ED), operating income per workload units (WLU) and operating income per air transport movement (ATM). This study determined the relationship between size/structure and key financial ratios.

With regard to the methodology used, Data Envelopment Analysis (DEA) is a non-parametric, linear programming model that has been extensively used in efficiency or performance evaluations. It provides relative measures of efficiency, using multiple inputs and outputs for a given Decision Making Unit or DMU without requiring a prior production function.

AIRPORT KEY ECONOMIC VALUE DRIVERS

The output of most efficiency frontier models has revolved around yearly number of airplanes, passengers and cargo, while inputs have commonly included runway length, passenger terminal area, number of employees and apron area. Also Lotti and Caetano (2018), when considering the variables for the choice of airports for the exportation of products, consider different airport costs, such as the costs of managing the cargo and airport charges, as well as the time of processing the cargo, related to the distance from the origin of the product to the airport. Barros (2008), Tovar and Cejas (2009), Coto-Milla et al. (2014) and Tsui et al. (2014) used those characteristics; however, Tovar and Cejas (2009) used a modified distance function instead of the most common Data Envelopment Analysis (DEA). Wanke (2014) expanded the input variable range to include figures for runways, aircraft parking spaces and vehicle parking spaces. In a word, the main goal of the aforementioned studies was to investigate operational efficiencies; they did not examine economic or financial efficiencies, which are the focus of the present study, with the purpose of adding a new dimension to those previous studies.

An even smaller number of studies have focused on determining an efficient frontier that combined operational efficiencies and economic drivers. Assaf (2010) kept the usual output profile while using labor price and capital price as inputs, as well as a Bayesian estimation method. Gitto and Mancuso (2012) divided their model so as to create what they called a physical model, which isolated airside activities, and a monetary model which also covered landside activities. Therefore, they innovated by defining their input model to include labor cost, capital invested and soft costs, whereas aeronautical and non-aeronautical revenues were defined as the model's output.

Labor cost, capital invested and operational costs were used as inputs by Barros and Dieke (2008) in their model. However, in their search for efficiency determinants, they used Simar-Wilson procedures. Additionally, Martin, Deniz and Dorta (2013) introduced and focused primarily on a key economic driver, i.e., cost, using an estimation of Stochastic Cost Frontiers. They tested cost flexibility in an economic downturn context and determined a cost frontier. Since results varied by geographic region, external variables on individual airport cost flexibility metrics were regressed against a common set of variables.

Malighetti et al. (2011) conducted regressions to deal with the revenue side of the efficiency equation, with the following coefficients: airport size, return on assets, leverage, passenger growth, airports within 100km, age and aviation revenues share. This particular study introduced ROA and debt into the equation. Table 1 lists the literature addressing operational efficiency and economic driver efficient frontier.

Table 1: Key Drivers Identified in the Literature

Authors	Index	Variables	Metrics
Assaf (2010)	Cost Efficiency	Input	Price of Labor
			Price of Capital
		Output	Number of Passengers
			Aircraft Movement
			Total Cargo
Barros (2008)	Technical Efficiency	Input	Labor
			Runways
			Airport Ramp
			Passenger Terminal Area
		Output	Number of Planes
			Number of Passengers
			Cargo
Barros and Dieke (2008)	Efficiency Determinants with Simar-Wilson procedure	Input	Labor Cost
			Capital Invested
			Operational Cost excluding labor cost
		Output	Number of Planes
			Number of Passengers
			General Cargo
			Receipt Handling
			Aeronautical Sales
			Commercial Sales
Fasone, Maggiore and Scuderi (2014)	Financial Analysis	Financial Indicators	Return on equity
			Return on investment
			Return on sales
			Asset turnover
			Equity on debt
			Operating income per WLU
			Operating income per ATM
		Efficiency Indicators	Cost of services per WLU
			Cost of services per ATM
			Cost of labor per WLU
			Cost of labor per ATM

Gitto and Mancuso (2012)	Technical Efficiency	Physical Model - Airside Airport Activities	Input: number of employees, runway area and airport area
			Output: Number of movements, passengers and cargo
		Monetary Model - Airside and Landside	Input: labor cost, capital invested and soft costs
			Output: aeronautical and non-aeronautical revenues
Malighetti et al. (2011)	Value Determinants	Size ROA Leverage Passenger growth Airports within 100 km Age Aviation revenues share Low-medium income country Upper-medium income country High income country	Financial Information
			Non-Financial Information
			Ownership Structure
			Industry Specific Regressors
Martin, Deniz and Dorta (2013)	Short-run cost Frontier	Variable Costs	Labor
			Materials
		Outputs	Domestic/international Passengers
			Air transport movements
			Average landed MTOW
			Metric tons of cargo
			Non-aviation revenues
		Fixed Factors	Gross floor area in terminal buildings
			Total runway length
			Total number or boarding gates
			Check-in desks
			Warehouse area
		Other	Time
			Full-time equivalent employees
			Index of airline traffic shares
			Share of charter traffic
			Share of low-cost traffic
			Ownership form

Millan et al. (2014)	Technical and scale Efficiency	Input	Number of employees
			Airport surface area
			Number of gates
		Output	Aircraft Movement
			Average Aircraft Size
			Share of non-aeronautical revenue in total airport revenue
Tovar and Cejas (2009)	Distance Function	Input	Number of employees
			Airport surface area
			Number of gates
		Output	Aircraft Movement
			Average Aircraft Size
			Share of non-aeronautical revenue in total airport revenue
Tsui et al. (2014)	Operational Efficiency	Input	Number of employees
			Number of runways
			Total runway length
			Passenger terminal area
		Output	Aircraft Movement
			Air Cargo volumes
			Air passenger numbers
Wanke (2014)	Efficiency Analysis	Input	Airport area
			Apron area
			Number of runways
			Total runway length
			Number of aircraft parking spaces
			Terminal area
			Number of parking places
		Output	Number of passengers
			Express cargo throughput
			Number of landings and take-offs

Source: research data

According to Table 1, it is possible to see that although scholars have been analyzing airport efficiency for decades, few studies have focused on the economic value driver aspects of these efficient frontiers.

DATA COLLECTION, ANALYSIS AND CLUSTERING METHODOLOGY

In the present study, the Data Envelopment Analysis (DEA) has been used, which is a non-parametric, linear programming model that has been extensively utilized for efficiency or performance assessments. It provides relative measures of efficiencies, using multiple inputs and outputs for a given Decision Making Unit (DMU) without requiring a prior production function. Charnes, Cooper and Rhodes introduced the DEA concept in 1978, and several studies, particularly in 1984 and 1999, further developed the method into its current, widely used form. Emrouznejad et al. (2008) provided a comprehensive list of more than 4,000 papers covering DEA and its multiples forms from 1978 to 2007. A comprehensive introduction to and analysis of DEA can be found in the studies of Thanassoulis (2001) and Zhu (2003).

Revenue as a single output was used by Barros and Dieke (2008), Tovar and Cejas (2009), Martin, Deniz and Dorta (2013), Gitto and Mancuso (2012), and it was already a development from the traditional operational efficiency frontier analysis. However, since it is a wide-ranging value driver – like operating cost and capital –, it is decided to include a second layer in this study. Ideally, each value driver should be further categorized according to their short, medium and long-term impacts, but these has not been a factor on this study.

This second layer was the main challenge in the study as it involved breaking the wide-ranging revenue value driver down into individual components. For example, the overall revenue had to be broken down into aeronautical and non-aeronautical revenues, and even further into vehicle parking, concessions fees, fuel fees and any other significant revenue sources, including real estate initiatives.

The key data sources were balance sheets, income and cash flow statements and, in a relevant way, management comments on financial reports. These data sources were the most used in the studies listed in Table 1. However, none of them looked into the individual components and used financial report top lines; in this respect, The study investigated the individual revenue components, thus providing a refined efficient frontier.

A second and indirect data collection method used consisted of finding key airport suppliers and searching their financial reports for the revenue derived in the airports studied.

One of the expected contributions of this study is to provide a basis for a comprehensive analysis of airport economic value drivers.

The restricted number of DMUs initially limited the number of variables in this study, as studied by Pedraja-Chaparro et al. (1999), Golany and Roll (1989), Banker et al. (1989), Friedmand and Sinuany-Stern (1998) and Cooper et al. (2007). Table 2 shows the recommended number of DMUs and variables for each author. On the other hand, Khezrimotlagh (2014) demonstrated in his study that a Kourosh and Arash Model (KAM) approach yields satisfactory results even when the number of DMUs in comparison with the number of variables does not follow the rules of the aforementioned studies.

Table 2: Number of DMUs (n) in relation to inputs (m) and outputs (p)

Pedraja-Chaparro et al. (1999)	n / (m + p) should not be small
Golay and Roll (1989)	n > 2 * (m + p)
Banker et al. (1989), Friedman and Sinuany-Stern (1998) and Cooper et al. (2007)	n > 3 * (m + p)
Dyson (2001)	n > 2 * m * p

Source: Khezrimotlagh (2014)

According to Table 2, the number of DMUs should be at least twice and up to three times the number of inputs and outputs combined.

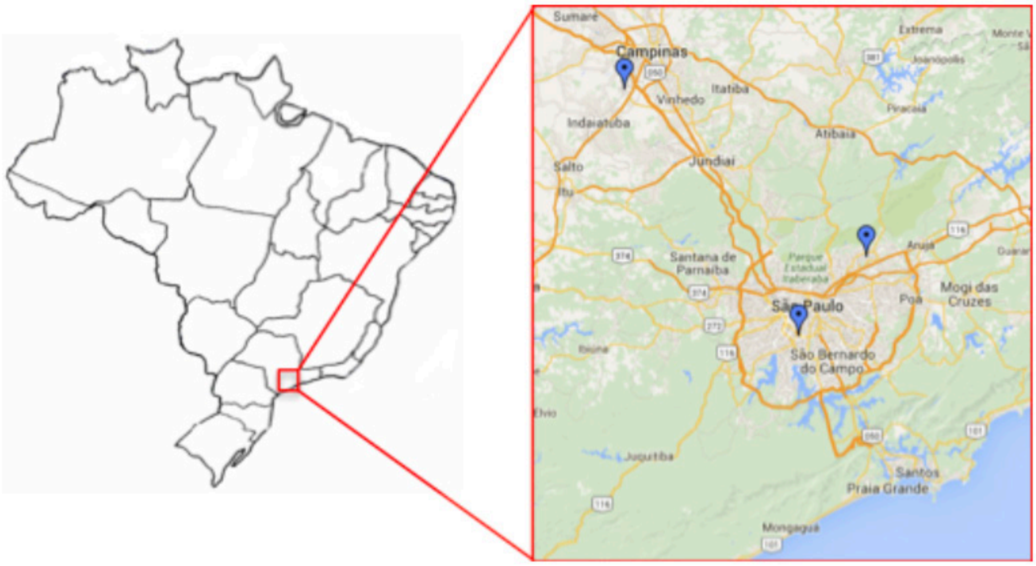
Data Envelopment Analysis results

Publicly available data has been used from several sources, using two different methodologies. Direct data was collected from airport operators such as Infraero and private operators at the recently concessioned airports; Agência Nacional de Aviação Civil (ANAC) and Secretaria de Aviação Civil (SAC) databases were also researched. These sources were also used by Rocha et al. (2016), Wanke (2012) and Fernandes et al. (2014).

The following Brazilian airports were analyzed: Congonhas Airport – CGH, in the city of São Paulo; Guarulhos International Airport - GRU (Sao Paulo's international airport); and Viracopos International Airport – VCP, in the city of Campinas, as shown in Figure 1. The availability of data varied by airport, ranging from the past 18 months up to the last 5 years, and included the items listed in Table 3.

For reference, GRU is ranked number one in Brazil in number of passengers, having reached approximately 39.5 million in 2014. CGH and VCP are ranked second and sixth, respectively, with 18.1 million and 9.8 million passengers in the same year (Infraero, 2015).

Figure 1: Airports analyzed (from left to right): VCP, CGH and GRU.



Source: adapted from Google Maps (2016)

Figure 1 shows the location of the airports analyzed, while Table 3 lists the variables analyzed.

Table 3: Main variables analyzed

Terminal area (m^2)	Concessions area (m^2)
Vehicle parking spaces (n)	Number of commercial concessions (n)
Apron and number of aircraft parking spaces (n)	Commercial revenue (BRL)
Cargo revenue (BRL)	Rent revenue including hangar spaces (BRL)
Fuel flowage fee (BRL)	Vehicle parking revenue (BRL)
Aeronautical revenue (BRL)	Marketing revenue (BRL)
Labor cost (Land- and Air-side) (BRL)	Administration costs (BRL)
Maintenance costs (BRL)	

Source: research data.

The initial set of DMUs included GRU, VCP and CGH, and all data corresponded to fiscal year 2014, except for CGH's airport terminal data, where 2015 data was used. The initial set of DMUs leaves sufficient room for future studies as 98% of the total number of passengers, around 199 million in 2014, used 65 airports. The selected inputs were Terminal Area, Number of Passengers per year and Operational Costs. For the first scenario, all outputs were financial and included Commercial Revenue, Passengers Vehicle Parking Revenue and Marketing Revenue.

Table 4 lists all data collected. However for the sake of confidentiality, an index was created so that the numbers listed therein are multiples of the original data.

Table 4: collected data

2014	A	B	C
Terminal Area	23,333.3	159,616.7	53,815.8
Area for Commercial Concessions (m^2)	5,566.7	-	9,111.6
Number of Passengers	8,205,710.8	32,947,500.0	15,112,306.7
Number of Car Parking Spaces	2,500.0	6,954.2	2,845.0
Number of Commercial Stores	-	189.2	60.8
Apron Area (m^2)	72,481.7	600,091.7	64,434.2
Number of Aircraft Parking Spaces	30.8	50.8	24.2
Commercial Revenue (million)	64.3	469.1	133.2
Cargo Revenue (million)	234.0	-	-
Fuel Flow Fee (million)	5.3	-	4.7
Car Parking Revenue (million)	17.4	86.0	6.5
Aeronautical Revenue (million)	86.9	-	128.8
Marketing Revenue (million)	3.9	46.9	13.2
Area Rental Revenue (million)	33.8	-	126.9
Other Revenue (million)	1.0	15,009.6	-
Non-Regulated Revenue (million)	-	910.7	-
Regulated Revenue	-	853.1	-
Operational Expenses (million)	217.7	179.7	-
Personnel Expenses (million)	108.8	-	70.5
Maintenance Expenses (million)	79.4	106.1	44.9
Other Operational Expenses (million)	29.5	148.6	12.3
Administrative Expenses (million)	-	95.8	2.3
Governmental Fee (million)	-	185.1	-

Source: research data

Table 4 lists all data collected and illustrates the wide range of financial reporting methods employed by the airport operators and the difficulty in extracting accurate and consistent data. Microsoft Excel Solver was used, through the LP Simplex engine, as this is recommended for linear problems. The following reports were generated for GRU, VCP and CGH, respectively.

Table 5 shows the inputs and outputs used for GRU's DEA, and since the efficiency index resulted in 1.00, that means that GRU is just as efficient as the other DMUs for this particular combination of variables. It shows that the airport is, given the limited number of common variables used, maximizing commercial, passenger parking and marketing revenues for its terminal area and number of yearly passengers, or minimizing its related costs.

Table 5: GRU' DEA

Name	Cell Value	Status	Slack
Passenger Terminal Area LHS	191,540.0	Binding	0
Number of Passengers Year LHS	39,537,000.0	Binding	0
Operational Cost LHS	148,600,000.0	Binding	0
Commercial Revenue LHS	562,860,000.0	Binding	-
Passenger Parking Revenue LHS	103,191,000.0	Binding	-
Marketing Revenue LHS	56,286,000.0	Binding	-
Weights Constraint LHS	1	Binding	0

Source: research data

In addition to being just as efficient as the other airports, Table 5 shows that all variables have zero slack, meaning that with this particular combination of variables, GRU could efficiently minimize inputs or maximize outputs in order to achieve total effectiveness. A slack number lower than 1.00 would mean that even if GRU acted to minimize inputs or maximize outputs, it would not achieve the efficiency level of the most efficient DMU.

Table 6 shows the inputs and outputs for VCP's DEA. Despite being almost four times smaller than GRU, it also had an efficiency index of 1.00, meaning that the airport is efficient for this combination of variables. It shows that the airport is maximizing its commercial, passenger parking and marketing revenues, given its terminal area and the number of yearly passengers, as well as minimizing its respective costs, again, given the limited number of common variables used.

Table 6: VCP's DEA

Name	Cell Value	Status	Slack
Passenger Terminal Area LHS	191,540.0	Binding	0
Passengers Yearly LHS	39,537,000.0	Binding	0
Operational Cost LHS	148,600,000.0	Binding	0
Commercial Revenue LHS	562,860,000.0	Binding	-
Passenger Parking Revenue LHS	103,191,000.0	Binding	-
Marketing Revenue LHS	56,286,000.0	Binding	-
Weights Constraint LHS	1	Binding	0

Source: research data

Table 6 also shows that all variables have zero slack, meaning that for this particular combination of variables, VCP could efficiently minimize inputs or maximize outputs in order to achieve total effectiveness.

With regard to CGH, Solver could neither find an optimal solution nor generate a feasibility report, meaning that the constraints can not be simultaneously satisfied. This is a common issue with models using significantly different scales, as is the case of this particular DMU. The difference in scale will trigger the model's instability as it tries to overcome accuracy requirements. Future analysis should try to rescale the variables and include a combination of other variables to avoid this situation.

As far as The results are concerned, similarly to Barros (2008) and Barros and Dieke (2008), who found significant variances in efficiencies in both studies mainly due to scale and location, the present study also indicates the need for a clustered DEA approach and further statistical analysis. Gitto and Mancuso (2012) also found similar results, indicating a greater sensitivity toward non-aeronautical revenues, which were the focus of this study.

The present study builds on the studies of Tsui et al. (2014), who also found that non-aeronautical revenues are key for an airport's efficiency, and, particularly, of Fernandes et al (2014), who also identified the need for a component-by-component analysis.

This study shows that, unlike previous studies focusing mainly on operational efficiencies, it is possible to examine whether an airport is maximizing its commercial, passenger parking and marketing revenues, given its terminal area and number of yearly passengers, using DEA methodologies. This study also provides the basis for various enhancements in efficient frontier analysis, including data selection, statistical tools and a DEA correlation analysis.

Recent developments in the Brazilian recently concessioned airports analyzed, mainly concerning their ability (or the lack thereof) to reach the expected Return on Investment (ROI), reached a bottom when both Campinas International Airport (VCP) and the Rio de Janeiro International Airport (GIG) virtually failed to pay their annual concession fees, while Guarulhos International Airport (GRU) formally asked for a payment reschedule.

What seems to be an inconsistency in this study reveals that the then short-term market outlook was largely overoptimistic. That outlook drove an extremely high winning bid, with annual concession fees, cost structure and mandatory investment schedule inconsistent with the situation of the enterprises and the economy. In other words, from a purely operating profit standpoint, this study is consistent with the fact that airport operators are mainly pointing to concession fees and mandatory investments as the underlying drivers of their financial performance as they are constantly adjusting their cost structure.

This is not directly explained by DEA, so the reader should to take into account that The analysis is a picture, rather than a dynamic present value study.

CONCLUSIONS

Airport operational efficiencies have been studied extensively, and although they are useful for indicating asset use patterns, previous studies do not take any economic or financial aspect into account. The present study recognizes that there are tradeoffs and, particularly, that an optimal balance has to occur between operation efficiencies and profitability, assuming that quality and safety are Pareto optimal.

In sum, this study used data for a few Brazilian recently concessioned airports, isolated their key financial-economic drivers, and employed an initial DEA methodology to build an introductory economic efficient frontier. We found several aspects which can be improved in future studies, from data collection and clustering to the statistical analysis. We chose DEA primarily because it is a deterministic and non-parametric methodology. Moreover, it can handle multiple inputs and outputs, even when they are presented in different units. DEA provides a relative measure of efficiency, which is the primary goal of this study, and has been used in a number of papers that examined operational efficiencies.

The main challenge to this deterministic DEA study was using different sources, thus possibly compromising the quality of collected data; in addition, the number of observations was limited, since Brazilian airport operators have different reporting standards. Enhancing this initial DEA methodology through Stochastic DEA, bootstrapping and frontier analysis should be considered for future studies.

The initial set of DMUs – i.e., CGH, GRU and VCP – provided a first look into economic efficient frontier, despite the limited number of variables. Two of the airports, GRU and VCP, were found to be efficient using this study's very limited combination of variables, meaning that theses airports are, from this standpoint alone, maximizing their commercial, passenger parking and marketing revenues, given their terminal area and number of yearly passengers. CGH analysis´ constraints could not be simultaneously satisfied. This is a common issue with models using significantly different scales, which was the case in this particular DMU. The difference in scale will trigger the model's instability as it tries to overcome accuracy requirements. Future analysis should try to rescale the variables and include a combination of other variables to avoid this situation.

Future studies should also expand this analysis on three distinct fronts: a) increasing the number of DMUs and cluster them by volume or location; b) conducting further statistical DEA analysis using bootstrapping, correlation adjustments and, perhaps, other stochastic elements; and, most importantly, c) examining and determining correlations yet to be studied between previous DEAs analysis focusing on operational efficient frontiers and this study's new economic efficiencies perspective. It is suggested the use of this methodology on ports and bus terminals to compare different results on transportation sciences.

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