Emerald Benchmarking: an International Journal

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Journal:	*Benchmarking: an International Journal*
Manuscript ID	BIJ-11-2020-0588.R2
Manuscript Type:	Original Article
Keywords:	Airlines, Latin America, Mergers & Acquisitions, Two-stage, Robust regression

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Structured Abstract

Purpose

The purpose of this study is to assess the efficiency determinants of mergers and acquisitions (M&A) in the context of Latin American airlines based on business-related variables commonly found in the literature. The idea is to identify preferable potential airline matches in light of fleet mix, ownership structure, and geographical proximity.

Design/Methodology/Approach

In order to achieve our objective, all possible combinations of M&A pairs are considered in the analysis, which is developed in a two-stage approach. First, the M&A Data Envelopment Analysis (DEA) model efficiency and returns-to-scale estimates are computed. Then, Robust Regression and Multinomial Logistic Regression are respectively used to discriminate these estimates in terms of such business-related variables.

Findings

The results reveal that these different contextual variables significantly impact virtual efficiency and returns-to-scale levels. Private ownership, passenger focus, and a better match between aircraft size and demand for flights appear to be key drivers for merged airline efficiency.

Research limitations/implications

The study makes theoretical contributions, though limited to analyzing Latin American airlines only. The use of bootstrapped robust/multinominal logistic regression, compared to the methods adopted by previous literature studies, generates more accurate and robust results related to the efficiency drivers due to its special feature and ability to allow the discrimination of increasing, decreasing, and constant returns to scale in light of a given set of contextual variables.

Practical implications

This study examines the pure effect of the merging activity on efficiency gains. Not only private ownership, but also a hybrid public-private ownership, have a positive influence on virtual efficiency, suggesting an important governmental role in promoting M&A in the airline industry.

Originality/value

We present an original take on the issue of airline mergers by exploring what are the major drivers possibly involved in efficiency gains of potentially merged (virtual) airlines. We identify preferable potential airline matches where efficiency gains would be positive in light of business-related variables such as fleet mix, ownership structure, and geographical proximity. Our analysis also includes an assessment of the impact of contextual variables such as cargo type, ownership structure, and geographical proximity in relation to the strategic fit of mergers considering the resulting efficiency and returns-to-scale scores of virtually merged airlines. To our knowledge, no previous research has addressed these issues in Latin American airlines. Further research directions for this industry are also discussed.

Keywords: Airlines; Latin America; M&A; two-stage; robust regression.

1. Introduction

Broadly speaking, the term "mergers and acquisitions" (M&A) refers to the process of merging or acquiring all or part of another company's property rights. An M&A is conducted under certain conditions in order to obtain controlling rights (Song and Chu, 2006). A merger or acquisition is an important strategic move made by a company to improve the performance of its enterprise management. Successful mergers can produce many gains, as verified in different economic sectors such as cost savings, increased profits, upscaling, and more abundant resources (Bernard *et al*., 2010; Johnes and Yu, 2008; Fried *et al*., 1999; Weber and Dholakia, 2000; Halkos and Tzeremes, 2013; Peyrache, 2013).

Consequently, there have been numerous studies in many developed economies examining the potential gains to be made from mergers (Shi *et al*., 2017; Gattoufi et al., 2014; Bogetoft and Otto, 2010; Bogetoft and Wang, 2005). However, to decrease the high failure rate of M&A activities, one of the critical steps that should be taken by a bidder company trying to identify suitable target companies prior to an M&A is to determine whether the prospective partner can offer synergies and the necessary relevant attributes to complement those of the takeover company. The need to make such M&A predictions has drawn the attention of many researchers in many industries around the world (Dietrich and Sorensen, 1984; Pasiouras and Gaganis, 2007; Powell, 2001; Gale and Shapley, 1962), including those focused on efficiency measurement (Chow and Fung, 2012).

In recent decades, airline mergers have been done around the world, leading to creating some of the world´s largest airlines (Yan *et al.*, 2016). The six airlines that have carried more than 100 million passengers in 2014 (American Airlines, Delta Air Lines, Lufthansa Group, Southwest Airlines, United Airlines, and China Southern Airlines) have all been involved in at least one major merger since 2000 (Center for Aviation [CAPA], 2015). In fact, many analytical and empirical studies have examined the effects of airline mergers, but the consensus is yet to be reached on fundamental issues such as market power and competition, network configuration, international competitiveness, and efficiency (Yan *et al.*, 2016), which is the focus of this study.

As regards market power and competition, the comprehensive literature review performed by Yan *et al.* (2016) suggests that increased market consolidation will not necessarily cause price increase unless a monopoly is created and competing airline entry is blocked. Conversely, where mergers involve small airlines, competition may be enhanced as a merged firm becomes more competitive. It is also possible that domestic mergers improve airline competitiveness when sufficient competition is maintained, but mergers leading to monopoly will remove incentives for airlines to improve, thus reducing their international competitiveness in the long run in a non-linear fashion (Oum *et al*., 2000).

With respect to network configuration, economies of density have been identified early in the airline industry (Brueckner and Spiller, 1991) with airline mergers often leading to higher traffic volumes that in turn allows using larger, more efficient aircraft, and also often allowing airlines to achieve higher load factors, and thus more intensive aircraft utilization. Fixed costs can also be spread over a larger output (Park, 1997). There is, however, a dynamic relationship between mergers, airline competition, and network configuration (Bilotkach *et al*., 2013; Luo, 2015) mainly related to consolidating existing hubs and/or establishing newer hubs to the detriment of old ones.

Regarding efficiency gains, merged airlines have the option of not only pooling resources such as personnel, aircraft, and ground facilities, but they also can rationalize and coordinate flight schedules, and expand their services across the inherent strengths of each part (Chen and Chen, 2003; Inglada *et al.*, 2006). According to Yan *et al.* (2016), studies strictly focusing on efficiency gains in airline mergers are not only scarce (e.g. Chow and Fung, 2012; Wang *et al.*, 2014; Yan *et al.*, 2015), but are also built upon traditional parametric and non-parametric techniques used in conventional airline efficiency studies. A non-comprehensive list of non-parametric and parametric efficiency methods and papers on airline efficiency may include the total factor productivity (TFP) approach (Bauer, 1990; Oum and Yu, 1995; Barbot *et al*., 2008), the Stochastic Frontier Analysis or SFA (Good *et al*., 1993; Baltagi *et al*., 1995), the Tornquist total factor productivity index (Coelli *et al*., 2003; Barbot *et al*., 2008), and DEA (Data Envelopment Analysis) models (Joo and Fowler, 2016; Merkert and Hensher, 2011; Barros *et al*., 2013; Barros and Peypoch, 2009; Barros and Couto, 2013). While previous studies have analyzed the impact of actual airline mergers in light of current production frontiers, they could not ascertain whether or not efficiency gains were uniquely derived from merging operations. In fact, efficiency levels could actually have improved without consolidation, being driven for instance by other regulatory or competitive issues (Yan *et al.*, 2016). In other words, the main issue from the literature lies in the fact that the previous studies did not attempt to differentiate the source of efficiency gains since the mix of the effect from the mergers with the influence of the external regulatory environment makes it difficult to assess the pure benefit of mergers. The investigation of the pure effect would be of particular importance and relevance considering the fact that the accurate estimates of this would provide valuable guidance in terms of the merging activities. Therefore, one of our main research questions in the current study would be what is the pure effect of the merging activity on efficiency?

This paper presents a different look at the issue of airline mergers by exploring with a predictive focus at the industry level what are the major drivers possibly involved in efficiency gains of potentially merged (virtual) airlines. The idea is to identify preferable potential airline matches where efficiency gains would be positive in light of distinct business-related variables such as fleet mix, ownership structure, and geographical proximity. This research focuses on the strategic fit of M&A as concerns Latin American airlines by using a DEA model variant as the cornerstone method to compute efficiency and returns to scale of virtually merged airlines. Besides, the present analysis includes an assessment of the impact of different contextual variables related to cargo type, ownership structure, and geographical proximity in relation to the strategic fit of M&As as regards the resulting efficiency and returns-to-scale scores of virtually merged airlines.

The Latin American locus was chosen because this region is relatively understudied in terms of its airline efficiency despite its importance to the world economy. In fact, Latin America is one of the world's most favored regions by the commodity price boom in the last ten years with a clear impact on airline traffic. However, most studies in the field have focused US airlines (Barros *et al*., 2013; Greer, 2008; Sjögren and Söderberg, 2011), Canadian airlines (Bauer, 1990; Assaf, 2009), European airlines (Distexhe and Perelman, 1994; Greer, 2008; Barros and Peypoch, 2009), Asian airlines (Baltagi *et al*., 1995; Wanke *et al*., 2015, Tavassoli *et al*., 2020), and African airlines (Barros and Wanke, 2015). Exceptions are the works of Melo Filho *et al*. (2014) who focused on Brazilian airline wages, while Oliveira and Huse (2009) focused on Brazilian airline price reactions to market entrants. Wanke and Barros (2016) investigated the efficiency of Latin American airlines using a two-step analysis combining both virtual frontier dynamic DEA and simplex regression. We are different from Wanke and Barros (2016) in the fact that we investigate not only the efficiency and relative drivers, but also the pure effect of the merging activity on efficiency gains. Most importantly, in the second-stage analysis we applied the robust regression analysis, which compared to the simplex regression analysis, allows the incorporation of two additional distributional assumptions for efficiency scores bounded between 0 and 1: Beta and Tobit distribution. This is justifiable because, a priori, no one can assure what is the exact distributional profile of efficiency estimates derived from non-parametric programming models. Besides, using bootstrapped multinomial logistic regression not only enhances the analysis as regards the resulting returns to scale of a given merged airline pair, but also allows the discrimination of increasing, decreasing, and constant returns to scale in light of a given set of contextual variables. Therefore, it would be able to provide more accurate and robust results in terms of the efficiency drivers.

To the best of our knowledge, this is the first time Latin American airlines have been analyzed at the industry level with respect to potential M&As. The contribution of this paper is that it is the first attempt at predicting the strategic fit of M&A in Latin American airlines in light of the innovative approach that is presented here.

The paper is structured as follows: after this introduction, Section 2 provides the contextual setting of the study including a description of Latin American airlines. A literature review is then presented in Section 3 followed by Section 4 – methodology in which the two-stage M&A DEA-Robust Regression/Multinomial Logistic Regression approach is presented and further discussed.

Section 5 presents our data followed by the discussion of results and conclusion in Sections 6 and 7, respectively.

2. Contextual Setting

Latin American airlines are organized under the ALTA association, which includes airlines from almost all Latin American countries. Table 1 presents the airlines analyzed.

[Insert table 1 here]

Table 1 shows that airlines from the largest Latin American economies (Brazil, Mexico, Argentina, and Chile) are represented in our sample. We also analyzed all major Latin American airlines. Aerolíneas Argentinas is Argentina's most important airline and is the national flag carrier. The company was created in 1949 and returned to government control in December 2014 after a brief period of private ownership. The Mexican airline Aeromar was established in 1987 and operates domestic services in Mexico and international services between Mexico and the US. Based at the Mexico City International Airport, Aeromar is a private airline owned by the Aeromar Group. The Mexican airline Aeromexico is that country's national airline and was established in 1934. With its hub in Mexico City International Airport, Aeromexico is a private airline held by a large number of private investors. Colombia's Avianca Airlines is that country's national airline. Established in 1919, it is one of the oldest airlines with its hub being located in Bogota, Colombia. Avianca has several subsidiaries: Avianca-Brazil, Avianca-Costa Rica, Avianca-Ecuador, Avianca-El Salvador, Avianca-Peru, and Avianca-Cargo. It is a private company owned by Germán Efromovich. The state-owned Bahamasair is the national airline of the Bahamas and was established in 1973. The airline Boliviana de Aviacion (BoA) is the publicly owned national carrier of Bolivia. Established in 2007, it flies to the US, Latin America, and Europe. Caribbean Airlines is a publicly owned airline that commenced operations in Trinidad and Tobago in 2006. Cayman Airways is the airline of the British Overseas Territory of the Cayman Islands. Founded in 1968, the airline is publicly owned. Copa Airlines of Colombia is a publicly owned national carrier and was established in 1993. Cubana de Aviación is the state-owned flag carrier airline of Cuba; founded in 1929, it serves most Latin American destinations. GOL, of Brazil, is a low-cost private airline operating out of São Paulo airport and began operations in 2001. InselAir of Curacao has been in business since 2006 and is the state-owned flag carrier. LATAM Airlines Group is a private airline from Chile that started operations in 2010. Based in Santiago, Chile, the company also has offices in São Paulo, Brazil. The company is the result of the merger of Brazil's TAM and Chile's LAN. LIAT, a company based in Antigua, is a Caribbean airline specialized in inter-island service. Operating since 1956, in 2007 this private airline merged with Caribbean Star Airlines. Chile's Santiago-based Sky Airline is a low-cost private airline serving Latin American destinations including Argentina, Brazil, Peru, and Bolivia. The company has been operating since 2002. TAME, of Ecuador, is the public flag carrier based in the international airport at Quito, founded in 1962. Volaris is a private Mexican airline headquartered in Tijuana, Mexico. The second-largest Mexican airline after Aeromexico, Volaris started operations in 2005. The above airlines are representative of most Latin American countries.

As regards previous airline M&A within Latin America, Caribbean Airlines acquired Air Jamaica, the national airline of Jamaica, in 2010. Avianca merged with SACO, a Colombian airline founded in 1933. In addition, LATAM airlines was created in 2010 by Chile's LAN Airlines when it completed a takeover of Brazil's TAM. After two years of negotiations, TAM shareholders agreed to the takeover. In 1958, the Chilean LAN bought LADECO (Línea Aérea del Cobre), a Chilean airline. The Brazilian TAM acquired Pantanal Airlines in 2009. Several earlier mergers and acquisitions have been observed in Latin America.

3. Literature Review

Most previous studies conducted to assess the effects of M&As on airline performance have mainly focused market power, regulation, competition, network configuration, and pricing issues rather than on the efficiency gains potentially produced by a merger. The same applies to more recent studies such as those conducted by Schosser and Wittmer (2015), Hüschelrath and Müller (2015), Wang *et al*. (2016), Wang *et al*. (2018).

The reasons for this focus in previous studies can be found in Yan *et al.* (2016) who presented a comprehensive literature review on the subject. The authors advocated that it is usually difficult for researchers to control dynamic factors related to market power, pricing, competition, regulation, and network configuration when computing the beneficial impact of mergers on efficiency levels. The analyses of M&A efficiency in the airline industry tend to be mostly inconclusive because of the complex nature of the myriad of factors that may affect performance. Hence, pure efficiency studies to assess the beneficial impacts of M&As in the airline industry are quite scarce. Some of them are discussed next.

Using the data between 2001-2010 in the Chinese airline industry, Yan *et al.* (2019) estimated the total factor productivity facilitated by both a non-parametric approach and a parametric method. The study further applied the difference-in-difference approach to evaluating the efficiency change of airlines. The findings suggest that mergers have a positive impact on productivity improvement in the Chinese airline industry. Ho *et al*. (2020) made an effort to further examine the impact of productivity efficiency and market power on the merged airline's wealth. Using the horizontal merger between China Eastern and Shanghai airlines in 2009, the study first computed the wealth effect of market power and productive efficiency in the airline mergers followed by the computation on the proportions of profit gains derived from market power and productive efficiency. The findings suggest that productive efficiency contributed 4 times more than the market power to the overall wealth gains of the merged airline. Most importantly, it shows that merger leads to productivity improvement. Other studies either used the SFA or non-parametric data envelopment analysis such as Yan *et al.* (2015) and Chen *et al*. (2017) with Hadi-Vencheh *et al*. (2020) yielding similar conclusions.

Differently from previous studies, this research investigates the impact of major contextual variables possibly involved in efficiency gains under a static controlled environment of (potentially merged) virtual airlines. The idea is to identify preferable potential airline matches in light of distinct business-related variables such as fleet mix, ownership structure, and geographical proximity by comprehensively testing the impact of all possible mergers, taken two by two, on the efficiency frontier of best practices.

Recently Wanke *et al*. (2015) and Barros and Wanke (2015) showed the importance of using efficiency methods with high discriminatory power towards the efficiency frontier meaning lower efficiency scores in contrast to traditional DEA models when assessing the efficiency of Asian and African airlines. In this research, this condition was achieved by a modified M&A DEA model that allows for comprehensive testing of all possible airline merger combinations in Latin

America in light of the current best practices frontier. As widely recognized, the higher the number of decision-making units (DMUs), the higher the discriminatory power of DEA models.

Additionally, we also advocate the combination of different predictive modelling techniques to effectively explore the impact of contextual variables on efficiency measurement. This paper innovates by proposing as a research tool an M&A DEA model combined with Robust Regression and Multinomial Logistic Regression with a two-stage approach. In this research, Robust Regression (RR) is used to handle efficiency scores of virtual companies contained within the interval between 0 and 1. RR is performed by a stochastic non-linear model solved by differential evolution that combines bootstrapped Simplex, Tobit, and Beta regression results. Multinomial Logistic Regression allows the discrimination of increasing, decreasing, and constant returns to scale in light of a given set of contextual variables.

4. Background on DEA models applied to M&As

DEA is a non-parametric model first introduced by Charnes *et al*. (1978). Based on linear programming (LP), it is used to address the problem of calculating relative efficiency for a group of DMUs by using a weighted measure of multiple inputs and outputs (Wanke, 2012). Consider a set of n observations on the DMUs. Each observation, DMU_j ($j = 1,\ldots,n$) uses m inputs x_{ij} ($i = 1,\ldots,m$) to produce s outputs y_{rj} ($r = 1,\ldots,s$). DMU_o represents one of the n DMUs under evaluation, and x_{io} and y_{ro} are the i^{th} input and r^{th} output for DMU_o, respectively. Model (1) presents the DEA model for the constant returns-to-scale (CRS) assumption under an input orientation (Zhu, 2003; Bazargan and Vasigh, 2003). If an additional constraint for summing up the lambda weights to one is imposed, varying returns-to-scale (VRS) is assumed.

$$
\begin{aligned}
&\theta^* = \min \theta \\
&S.T. \\
&\textstyle\sum_{j=1}^{n} x_{ij}\lambda_j \le \theta x_{io} \qquad i = 1,2,\ldots,m; \qquad\qquad (1) \\
&\textstyle\sum_{j=1}^{n} y_{rj}\lambda_j \ge y_{ro} \qquad r = 1,2,\ldots,s; \\
&\lambda_j \ge 0 \qquad\qquad j = 1,2,\ldots,n;
\end{aligned}
$$

Any of the DMUs may or may not be on the frontier when the output-input ratio is measured (Barros and Peypoch, 2009; Wang *et al.*, 2012; Wang and Feng, 2015). The distance from the actual location of a particular DMU to the frontier is believed to represent the inefficiency of the DMU, which may be caused by various factors that are specific to the DMU. If the efficiency of DMU *i* is 1, DMU *i* is a technically efficient DMU; if its efficiency is less than 1, it is technically inefficient. As depicted in Table 2, using the data on how much aircraft and employees each airline uses to produce a given number of flights, Model 1 is used to ascertain whether it is possible, in the case of each airline, for it to produce the same level of output as it produces in a given year while using proportionally less of each of the two inputs.

DEA has been recently applied to M&A studies with various pieces of research aimed at analyzing the gains in efficiency of an M&A have been conducted. For example, Bogetoft and Wang (2005) built economic production models using a DEA approach to estimate the potential efficiency gains from mergers. Lozano and Villa (2010) also proposed a DEA-based approach to estimate the efficiency gains resulting from a merger. Other studies (Halkos and Tzeremes, 2013; Peyrache, 2013; Lo *et al*., 2001; Liu *et al*., 2007) also applied DEA in an M&A context. DEA is also a useful tool when judging a firm's size in an M&A context. Researchers such as Wu *et al*. (2011) established a greedy algorithm based on a DEA approach. They aimed to choose the proper candidate company for a bidder company from the perspective of the firm's size when considering an M&A. Lin *et al*. (2008) proposed a framework consisting of both efficiency and risk analyses. Their framework allows the simulation of pro forma mergers and hence the determination of the optimal number of firms in the industry by using a DEA approach. However, an empirical study (Chapin and Schmidt, 1999; Harris *et al*., 2000) found that efficiency gains do not happen with a return to scale in most cases. Therefore, the fit of an M&A should not only focus on efficiency gains, but it should also prevent scale oversize by the M&A.

Suppose there are n companies in the market, which can be treated as n DMUs to be evaluated as potential bidders with a potential option of acquiring (n - 1) targets. All possible merger combinations are assessed for each year. Since there are 19 airlines in our sample for each year, a total of 19*18/2 = 171 possible merger schemes are assessed. The combination between an arbitrary bidder airline, say DMU_d, $d \in \{1,\ldots,n\}$ with an arbitrary target airline, say DMU_k, $k \in$

{1,...,n}, d and k being different, is regarded as an M&A fit scheme or a virtual company resulting from a possible M&A, say $DMU_{d\&k}$.

For each one of the possible mergers, two efficiency evaluation models are presented next. The first model (Model 2) is used to determine the relative efficiency of $DMU_{d\&k}$ in light of the current best practices frontier. Readers should note two slight differences between Models 2 and 1. First, a unique value of θ (*theta)* and λ (*lambda)* is assigned to the merged $DMU_{d\&k}$ under assessment. This would be the equivalent of imposing a unique weighted value of *theta* and *lambda* for each one of the DMUs d and k under analysis and for their sum if Model 1 were being used (that is, $\lambda_k = \lambda_d = \lambda_{d\&k}$ and $\theta_k = \theta_d = \theta_{d\&k}$). Second, Model 2 observes the CRS assumption, which means that the summation of *lambda* values is not restricted to one. At this point, it is important to note that the input-oriented efficiency Model 2 is solved by minimizing the inputs of this new hypothetical $DMU_{d\&k}$ while maintaining its outputs as the sum of the pre-merger level. In the approach developed here, differently from previous papers (e.g. Shi *et al*., 2017; Gattoufi *et al*., 2014), CRS is considered as the underlying assumption in Model 2, therefore making sure that the hypothetical merged $DMU_{d\&k}$ does not surpass the original production possibility set used to compute the individual efficiency pre-merger scores. Hence, to evaluate the efficiency of $DMU_{d\&k}$ and provide an initial assessment on its return to scale (RTS), the following linear programming model is proposed:

$$\begin{aligned}
&\text{Min } \theta_{d\&k} \\
&\text{s.t.} \quad \begin{cases} \sum_{j=1, j \neq k,d}^{n} \lambda_j x_{ij} + \lambda_{d\&k}(x_{ik} + x_{id}) \leq \theta_{d\&k}(x_{ik} + x_{id}), \\ \sum_{j=1, j \neq k,d}^{n} \lambda_j y_{rj} + \lambda_{d\&k}(y_{rk} + y_{rd}) \geq y_{rk} + y_{rd}, \\ j = 1,2,\ldots, n;\; k = 1,2,\ldots,n;\; d = 1,2,\ldots,n;\; j \neq d \neq k, \\ \lambda_j,\;\; \lambda_{d\&k} \geq 0;\; i = 1,2,\ldots,m; r = 1,2,\ldots,s \end{cases}
\end{aligned} \tag{2}$$

where $\hat{\lambda}_j$ and $\hat{\lambda}_{d\&k}$ are the optimal solutions to the above model.

The second model (Model 3), which is described next, is used in an auxiliary way to assess whether returns to scale of the resulting virtual companies are increasing, decreasing, or constant. Readers should note that Models 2 and 3 may yield multiple optimal solutions simultaneously. The following approach is adopted here in order to avoid conducting quadratic programming for Model 2.

Let $\hat{W} = \sum_{j=1,\, j \neq k,d}^{n} \hat{\lambda}_j + \hat{\lambda}_{d\&k}$. If $\hat{W} < 1$, as obtained from Model 2. The following model may be applied to avoid exploring all alternate optima:

$$
\begin{aligned}
\text{Max} \quad & \sum_{j=1,\, j \neq k,d}^{n} \hat{\lambda}_j + \hat{\lambda}_{d\&k} \\
\text{s.t.} \quad & \sum_{j=1,\, j \neq k,d}^{n} \hat{\lambda}_j x_{ij} + \hat{\lambda}_{d\&k}(x_{ik} + x_{id}) \leq \theta^*(x_{ik} + x_{id}), \\
& \sum_{j=1,\, j \neq k,d}^{n} \hat{\lambda}_j y_{rj} + \hat{\lambda}_{d\&k}(y_{rk} + y_{rd}) \geq y_{rk} + y_{rd}, \\
& \sum_{i=1,j \neq k,d}^{n} \hat{\lambda}_j + \hat{\lambda}_{d\&k} \leq 1, \\
& j = 1,2,\ldots,n;\; k = 1,2,\ldots,n;\; d = 1,2,\ldots,n;\; j \neq k \neq d, \\
& \hat{\lambda}_j, \hat{\lambda}_{d\&k} \geq 0;\;\; i = 1,2,\ldots,m;\; r = 1,2,\ldots,s,
\end{aligned} \tag{3}
$$

If $\hat{W} > 1$, Model 4 works in a similar fashion as Model 3 with an adjustment in the inequality of the third constraint.

$$
\begin{aligned}
\text{Max} \quad & \sum_{j=1,j \neq k,d}^{n} \hat{\lambda}_j + \hat{\lambda}_{d\&k} \\
\text{s.t.} \quad & \sum_{j=1,j \neq k,d}^{n} \hat{\lambda}_j x_{ij} + \hat{\lambda}_{d\&k}(x_{ik} + x_{id}) \leq \theta^*(x_{ik} + x_{id}), \\
& \sum_{j=1,j \neq k,d}^{n} \hat{\lambda}_j y_{rj} + \hat{\lambda}_{d\&k}(y_{rk} + y_{rd}) \geq y_{rk} + y_{rd}, \\
& \sum_{j=1,j \neq k,d}^{n} \hat{\lambda}_j + \hat{\lambda}_{d\&k} \geq 1, \\
& j = 1,2,\ldots,N;\; k = 1,2,\ldots,t;\; d = 1,2,\ldots,h;\; j \neq k \neq d, \\
& \hat{\lambda}_j, \hat{\lambda}_{d\&K} \geq 0,\; i = 1,2,\ldots,m;\; r = 1,2,\ldots,s,
\end{aligned} \tag{4}
$$

where θ^* is the optimal solution to $\theta_{d\&k}$ determined by Model 2, $\hat{\lambda}_j^*$ and $\hat{\lambda}_{d\&k}^*$ are the optimal solutions to Models 3 and 4.

Let $\hat{W}^* = \sum_{j=1, j \neq d,k}^{n} \hat{\lambda}_j^* + \hat{\lambda}_{d\&k}^*$, which is used for RTS evaluation (Banker and Thrall, 1992). The following conditions identify the respective RTS condition:

(1) The RTS of $DMU_{d\&k}$ is increasing if $\hat{W}^* < 1$. This situation shows that the resulting virtual company can be larger after M&A, although still preserving increasing RTS. In other words, this is a situation where the productive resources of the virtual company are still less than the demand it faces.

(2) The RTS of $DMU_{d\&k}$ is decreasing if $\hat{W}^* > 1$. This situation shows that the M&A may lead to the resulting virtual company becoming oversized in scale and therefore too big in terms of the productive resources for its current level of demand.

(3) The RTS of $DMU_{d\&k}$ is constant if $\hat{W}^* = 1$. This situation shows that the M&A may not lead to the resulting virtual company becoming either over or undersized in scale, although larger in terms of productive resources and demand when compared to the original companies in isolation.

Results for the 171 possible merger combinations for 2014 are given in Table A1 in the Appendix for illustration. The mean absolute percent difference between $\hat{W}^*$ and $\hat{W}$ is 13.62%.

5. Data and efficiency assessment

5.1. The data

The data on 19 Latin American airlines were obtained from the Alta airline website based on available operational reports of airlines for the period 2010 to 2014 (https://www.alta.aero/la/home.php). The final sample size of 95 units involves the combination of 19 airlines for five years. Inputs and outputs adopted in this research were in accordance with the literature and data availability. As inputs we used the number of employees and the total number of aircraft. The single output was represented by the total number of domestic and international flights. Their descriptive statistics are presented in Table 2 and their correlation matrix given in Table A2 in the Appendix suggests isotonicity.

In addition, seven original contextual variables were collected to explain the differences in efficiency levels. These are also presented in Table 2 and are related to the major business characteristics of the airline, namely: ownership type (whether public [1] or not [0]), whether the airline performs cargo transportation (1) or not (0), the fleet mix of the airline (percentage of large and small aircraft), and the percent of domestic flights. Besides, two contextual variables were also used to represent the linear and squared components of a possible learning curve.

This set of original contextual variables was then transformed so it could appropriately reflect the M&A strategic fit for each pair of airlines considered as potential candidates for forming a virtual company. The following set of secondary contextual variables was also defined:

- *Share borders* or whether the respective countries of the merged airlines are neighbors – [1] or not [0]
- *Same country* or whether both merged airlines belong to the same country – [1] or not [0]
- *Ownership structure* or whether dominant public in the case both merged airlines are public, dominant private in the case both merged airlines are private, or hybrid in the case one company is private and the other public or vice-versa
- *Focus on cargo operation* or whether strong in the case both merged airlines perform cargo transportation, weak in the case only one company is focused on cargo transportation, or inexistent in the case neither company operates cargo transportation

Fleet mix and percentage of domestic flights were also recomputed in light of the M&A and an average linear and squared trend was considered for each case.

[Insert table 2 here]

Simar and Wilson (2011) examined the widespread practice where efficiency estimates are regressed on some environmental variables in what is commonly known as a two-stage analysis. The authors argue that this is done without specifying a statistical model in which such structures would follow from the first stage where the initial DEA estimates are obtained. As such, these two-stage approaches are not structural, but rather *ad hoc*. The most important underlying assumption regarding two-stage analysis is the one on global separability (Kourtesi *et al*., 2012). This assumption is described next.

In general terms, the vector of environmental factors or contextual variables, Z, may either affect the range of attainable values of the inputs and outputs (X, Y) including the shape of the production set, or it may only affect the distribution of inefficiencies inside a set with boundaries not depending on Z, meaning that only the probability of a DMU being less or more distant from the efficient frontier may depend on Z, or both (Bădin *et al*., 2012). Under separability, the environmental factors have no influence whatsoever on the support of (X,Y) and the only potential remaining impact of the environmental factors on the production process may be on the distribution of the efficiencies.

To understand the importance of the "separability" condition, let X ∈ Rp + denote a vector of p input quantities and let Y ∈ Rq + denote a vector of q output quantities. In addition, let Z ∈ Z ⊆ Rr denote a vector of r environmental variables with domain Z. Let Sn = {(Xi, Y i,Zi)}ni =1 denote a set of observations. The separability assumption in Simar and Wilson (2011) implies that the sample observations (Xi, Yi, Zi) in Sn are realizations of identical, independently distributed random variables (X, Y, Z) with probability density function f (x, y, z), which has supported over a compact set P ⊂ Rp+q+ × Rr with level sets P(z) defined by P(z) = {(X, Y) | Z = z, X can produce Y }. Now let F = U P(z) ⊂ Rp+q, z∈Z. Under the "separability" condition, P(z) = F ∀ z ∈ Z and hence P = F × Z. If this condition is violated, then P(z) is different than F for some z ∈ Z. Whether this is the case or not is ultimately an empirical question to be assessed within the scope of each research case.

Daraio *et al*. (2010) provided a method for testing H0 : P(z) = F ∀ z ∈ Z versus H1: P(z) is different than F for some z ∈ Z. In order to test these null hypotheses, consider the test statistics $\tau_{Frontier,n}(S_n) = n^{-1}\sum_{i=1}^{n} \hat{D}_{Frontier,i}\, \hat{D'}_{Frontier,i} \geq 0$ where $\hat{D}_{Frontier,i} = (Y_i\, \hat{\lambda}_{Frontier}(X_i, Y_i / S_n) - Y_i\, \hat{\lambda}_{Frontier}(X_i, Y_i / Z_i, S_n))$ and its complementary $\hat{D'}_{Frontier,i}$ are (q × 1) vectors. These statistics give estimates of the mean integrated square difference between P and F × Z. If the separability assumption holds, we should expect these statistics to be "close" to zero, otherwise we should expect them to be "far" from zero.

In this research, an R code was structured using the packages *np (*Hayfield and Racine, 2008) and FNN (Beygelzimer *et al*., 2015) to compute these test statistics, which are presented in Table A3 in the Appendix. In situations where the separability condition is satisfied, it would be straightforward to perform the second stage analysis. For instance, one might estimate the regression model by the maximum-likelihood method using standard software (Simar and Wilson, 2011). Besides, readers should note that under standard assumptions where properties of traditional

DEA estimators have been derived, the mass of estimates equal to one may negatively affect this test statistic, leading to values far from zero.

5.2. Robust Regression Approach

In this research, the impact of the contextual variables related to the merging of Latin American airlines is tested by a robust regression approach. In this approach, Tobit (Wanke et al., 2016a), Simplex (Wanke and Barros, 2016), and Beta regressions (Wanke et al., 2016b) individually designed to handle dependent variables bounded in 0 and 1 are combined by means of stochastic non-linear programming and bootstrapping. This is justified because most regression approaches produce biased results in two-stage DEA approaches since they do no often take into account the underlying issues caused by the lack of discriminatory power of the scores computed in the first stage (Wanke et al., 2016c). The discriminatory power is low because efficiency scores tend to be upward-biased towards one. Therefore, a robust regression approach should reflect an adequate distribution assumption in order to handle this type of bias. This may be obtained by bootstrapping (Simar and Wilson 2007, 2011) and combining forecasts to yield smaller prediction errors (James *et al*., 2013, Ledolter, 2013).

In fact, researchers frequently face situations where they are interested in modelling proportions, percentages, or values such as efficiency scores within the interval (0; 1) according to one or several covariates and within the architecture of the regression. For this type of variable, the underlying Gaussian assumption in Tobit regression maybe not supported if scores are upward-biased, thus invalidating conclusions that might be obtained from these results. Asymmetry of the response variable and multicollinearity are two of the most frequent problems that the Gaussian assumption cannot accommodate. In this situation, several alternatives have been developed such as Beta regression, which leverages the advantages of the general linear model, the Simplex distribution, which is part of a more general class of models, i.e., the dispersion models (López, 2013).

The non-linear stochastic optimization problem for the combination of Beta and Tobit bootstrapped regressions is presented in Model 5 where *w1* represents the weight assigned to the residuals of the Tobit regression (***Rt***), *w2* represents the weight assigned to the residuals of the Simplex regression (***Rs***), and ***Rb*** represents the residuals of the Beta regression. This model optimizes the values of *w1* and *w2* so that the variance (*Var*) of the combined residuals is minimal.

These three regressions were bootstrapped and combined 200 times so that a distribution profile of *w1* and *w2* could be collected for the virtual efficiency predictions of merged airlines.

$$\min Var(w1\boldsymbol{Rt} + w2\boldsymbol{Rb} + (1 - w1 - w2)\boldsymbol{Rs})$$
$$S.T.$$
$$w1 \leq 1$$
$$w1 \geq 0 \qquad (5)$$
$$w2 \leq 1$$
$$w2 \geq 0$$
$$w1 + w2 \leq 1$$
$$w1 + w2 \geq 0$$

Model 5 was solved using the differential evolution (DE) technique. DE is a member of the family of genetic algorithms that mimics the process of natural selection evolutionarily; see Holland (1975). A genetic algorithm solves optimization problems with biology-inspired operators of crossover, mutation, and selection generating successive populations of individuals (solutions or generations). In addition, the DE algorithm finds the global optimum of the objective function, which does not require to be either continuous or differentiable; see Thangaraj *et al*. (2010) and Mullen *et al*. (2011). The R package named DEoptim implements the DE algorithm and was first published on CRAN in 2005. Interested readers should refer to Ardia *et al*. (2011) and Mullen *et al*. (2011) for a detailed description of the package.

5.3. Predicting returns to scale using Multinomial Logistic Regression

Logistic regression is a generalization of linear regression used for predicting dichotomous or multi-class dependent variables (Hosmer and Lemeshow, 2000). It assumes that the response variable is linear in the coefficients of the predictor variables. Its main advantage is a simple probabilistic formula for classification. In this research, in order to explain the three different RTS groupings after evaluating all possible M&A fit schemes as defined in Section 4 by taking the original companies 2 by 2, multinomial logistic regression analyses were performed considering the contextual variables as predictor variables. Similarly, bootstrapping was also performed on the multinomial logistic regression. A resample size of 200 was considered.

6. Results and Discussion

6.1. Preliminary analysis on Latin American Airlines (traditional DEA model)

Initially, input-oriented DEA VRS estimates revealed the existence of 28 efficient observations out of 95 from 2010 to 2014. The median efficiency score was 0.839. The majority of observations, 52, presented decreasing returns-to-scale. Only two observations presented constant returns-to-scale, while 41 presented increasing returns-to-scale. The distribution of the efficiency scores obtained running Model 1 is given in Fig. 1.

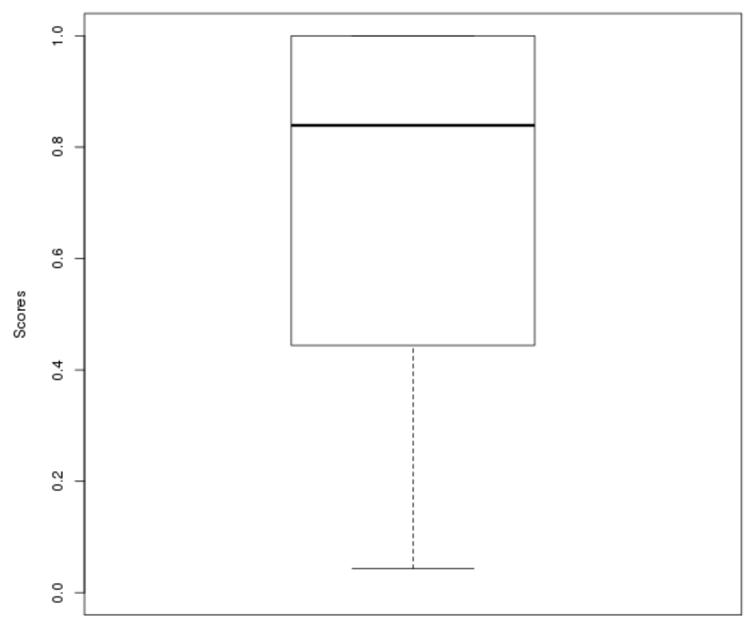

Fig. 1 - Box plot of DEA-VRS efficiency scores distribution

As regards the distributional fits of the DEA-VRS efficiency scores in Latin American airlines, Fig. 2 depicts the Gaussian (Tobit), the Simplex, and the Beta adjustments for their inverse cumulative distributions. Although it may seem possible to state at first sight that the Beta distribution is preferable to the other two, there might be unanticipated circumstances where pooling distributions could be beneficial in terms of a better adjustment and forecasting. In fact, results for the Kullback-Leibler (KL) divergence presented in Table 3 indicate that differences between these three types of adjustments are relatively small, particularly between Simplex and Gaussian assumptions, which may eventually favor one distributional assumption, that is one specific regression type, to the detriment of the other. The closer to zero, the better is the KL divergence. This is explored now by the robust regression approach.

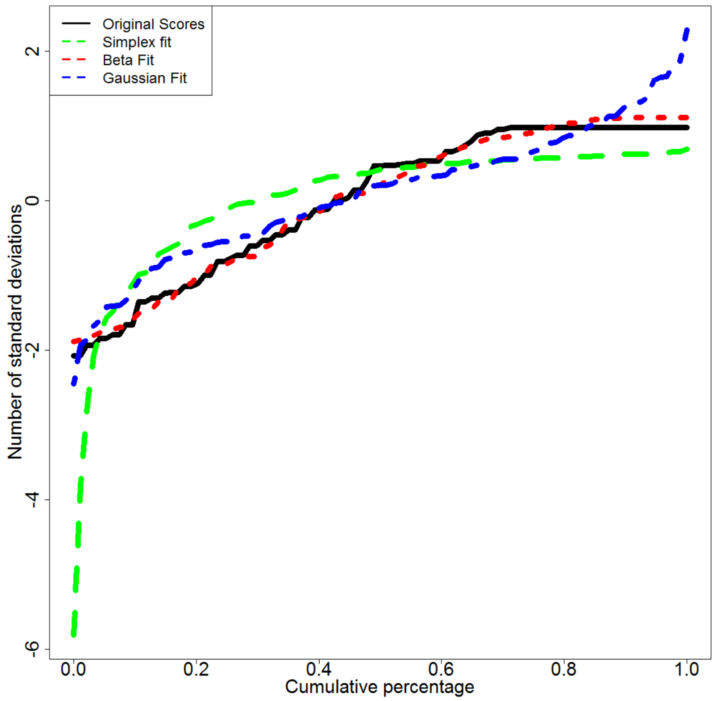

Fig 2 - Inverse cumulative distributions for the DEA-VRS efficiency scores

[Insert table 3 here]

The results for the stochastic non-linear optimization on the 200 bootstrapped Tobit, Simplex, and Beta regression residuals are presented in Fig. 3. It suggests an almost even split of the weighs between these three distributional assumptions in accordance with Table 3 results.

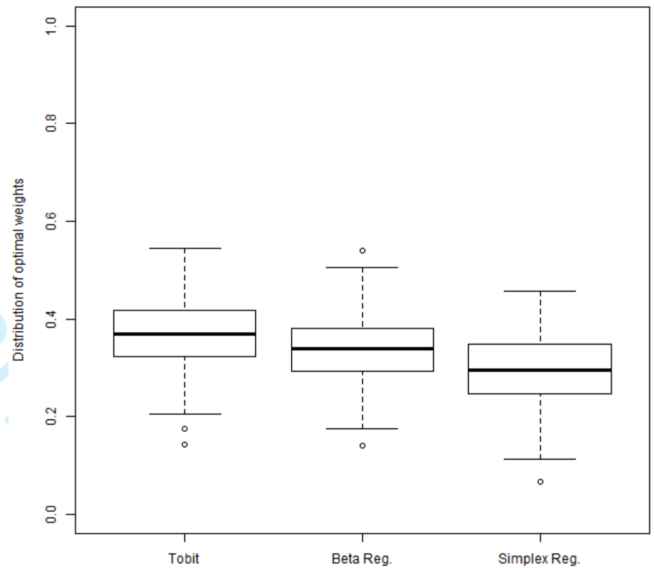

Fig 3 - Distribution on the optimal values of *w1* and *w2* for each efficiency distribution

The impact of contextual variables on airline efficiency in Latin America is presented in Fig. 4. Readers should note the solid black line that crosses the estimates for each contextual variable in zero. Contextual variables are found to be positively (negatively) significant when the dispersion for their bootstrapped estimates, given by the vertical dashed lines, is completely located above (below) the respective horizontal solid line. Results suggest that public airlines and airlines that operate both passenger and cargo transportation are less efficient in turning the number of aircraft and employees into the number of flights. Although the negative impact of public ownership on airline efficiency levels corroborates previous studies, a possible explanation for the negative impact of both cargo and passenger operation could be a limitation in the number of destinations that are economically feasible to be served by air cargo transportation companies. Besides, a large percentage of domestic flights appears to be significantly limiting the network span of the airline, thus possibly implying fewer flights per employee and aircraft when compared to other airlines that fly international destinations. On the other hand, a large percentage of small aircrafts significantly and negatively impacting efficiency levels may denote insufficient flight demand given the airline current level of resources, as may be the case for some state-owned companies that operate island to island air transport in the Caribbean.

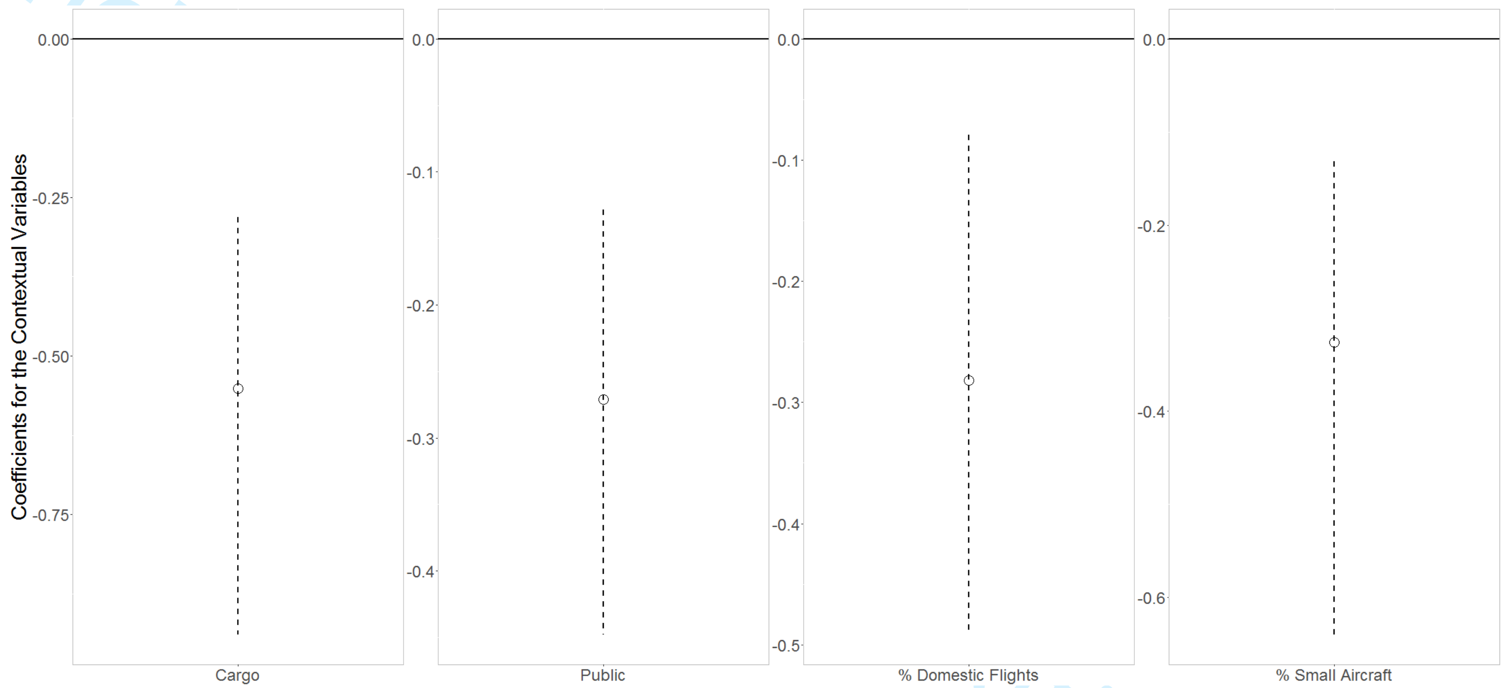

Fig 4 - Combined bootstrapped regression results for efficiency scores in Latin American airlines

Results for the RTS classification and prediction in light of the contextual variables are depicted, respectively, in Figs. 5 and 6 after performing 200 bootstrapped interactions for the Multinomial Logistic Regression. Readers should note that after removing any forecast classification bias bootstrapping, decreasing returns to scale still prevails in Latin American airlines, but less numerously with a median of around 37% of cases. DRS is followed, in order, by increasing and constant returns-to-scale, which presented a substantial increase to almost a third of the sample, thus denoting an operation at the most productive scale size region. On the other hand, this result also suggests that more than a third of Latin American airlines analyzed seems to be too small in terms of aircraft and employees when compared to the current number of flights they perform.

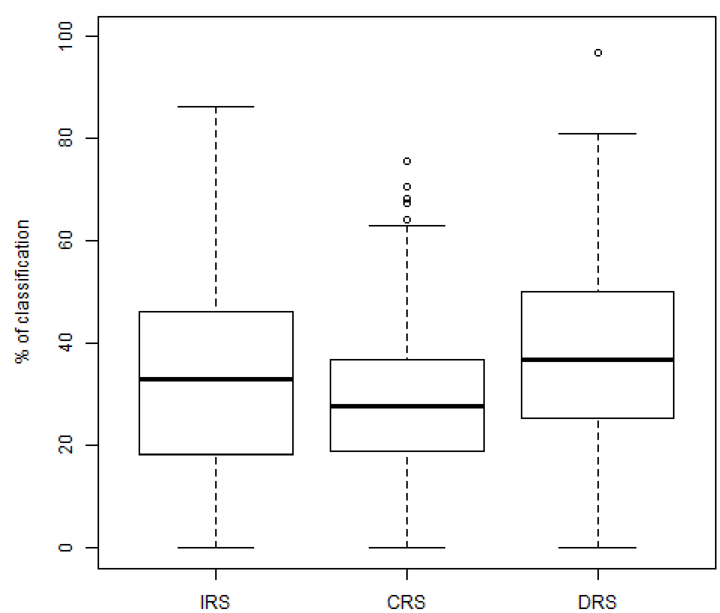

Fig 5 - RTS classification distribution of Latin American Airlines

Results for the bootstrapped multinomial logistic regression coefficient estimates are presented in Fig. 6. They indicate the discrimination between the two groups formed by CRS and DRS Latin American airlines against the group formed solely by IRS Latin American airlines (category of reference). No contextual variable was found to be significant, thus leading to inconclusive results with respect to RTS discrimination given the current set of contextual variables. On the other hand, these results may suggest that IRS, DRS, and CRS operations are somehow evenly split throughout these different groupings, i.e., public/private, cargo/non-cargo, focused/not focused on domestic flights, etc.

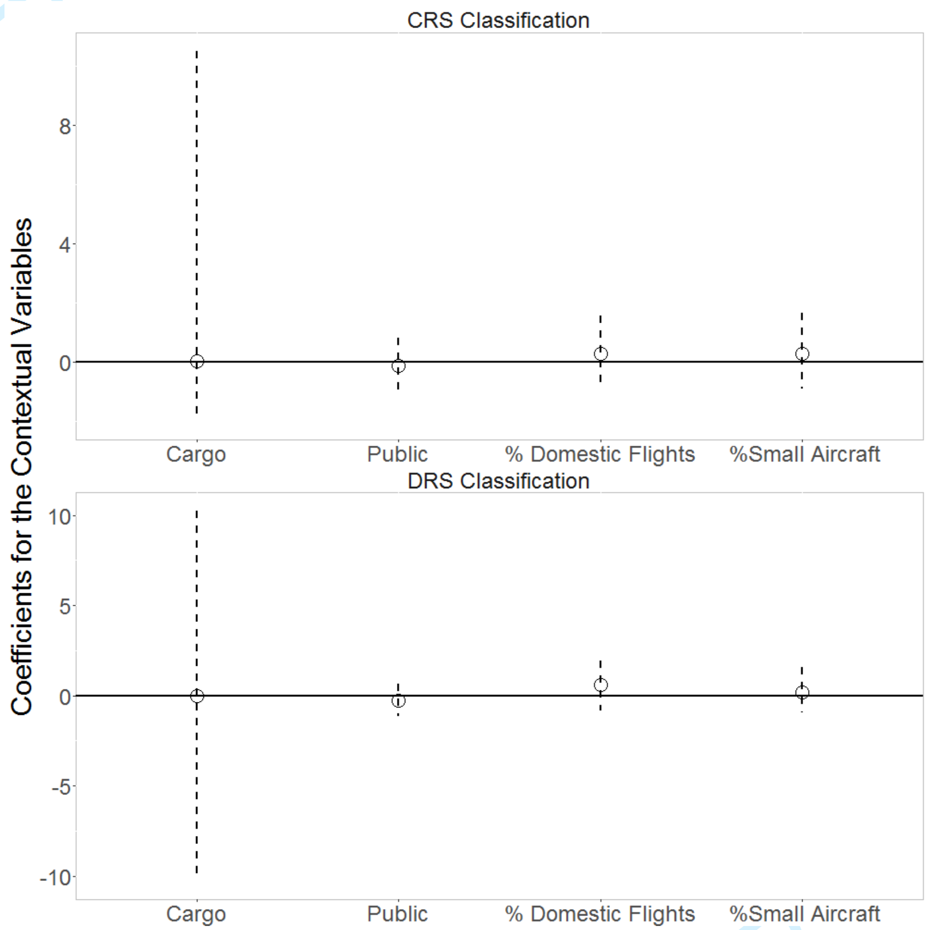

Fig 6 - RTS prediction by bootstrapped multinomial logistic regression

6.2. Analysis of M&As in Latin American Airlines

The results for the M&A DEA efficiency scores as depicted in Fig. 7 for all possible combinations taken 2 by 2 revealed the existence of 155 efficient observations out of 855 (171*5) between 2010 and 2014. The median efficiency score was 0.872, a slight increase when compared to the median of the original, pre-merger, scores. Again, the majority of observations presented decreasing returns-to-scale, but in a higher proportion, 63.75%. Only 0.47% and 35.79% of the observations presented, respectively, constant and increasing returns-to-scale. The comparative distribution of the efficiency scores obtained running Model 2 is given in Fig. 7.

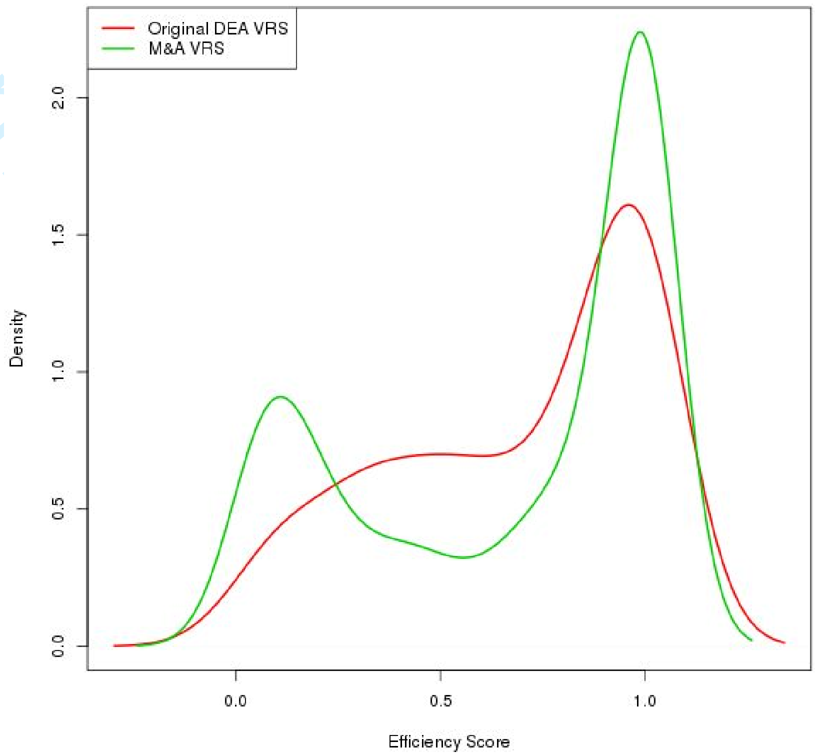

Fig. 7 - M&A DEA-VRS efficiency scores distribution

Similarly to what was done in the previous section, M&A efficiency scores were analyzed in light of the three distributional assumptions and weights were assigned within the ambit of the bootstrapped robust regression by non-linear stochastic programming. While Fig. 8 left and Fig. 8 right depict the results for the distributional analysis and fit respectively, Table 4 displays the KL divergence results. Although the Gaussian fit is outperformed by far by the Beta and Simplex assumptions, there is a region around the 40th percentile where it stands very close to the original scores. Differently from what was found in the previous analysis, it is not possible to say that an even split of weights occurred among these three assumptions with a clear advantage to Simplex, which presented the best fit to the M&A scores.

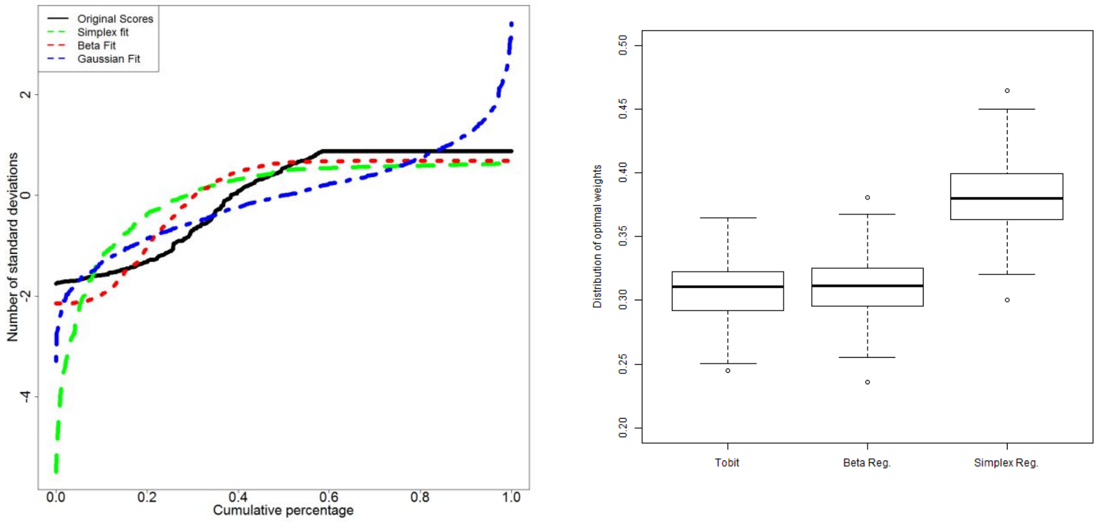

Fig. 8 - Distributional analysis (left) and fit (right)

[Insert table 4 here]

The results for the bootstrapped robust regression approach presented in Fig. 9 partially confirm previous findings for the original airlines. Not only is it still possible to affirm that merged airlines with elements of a private administration ("private ownership" and "hybrid ownership") are more efficient than public ones, but it is also possible to affirm that merged airlines that operate both passenger and cargo transportation are less efficient in turning the number of aircraft and employees into the number of flights. Besides, although it is not possible to affirm that the geographical location has a significant impact on merged airline efficiency since the coefficients for "share borders" and "same country" were not significant, a higher percentage of domestic flights still appears to be a relevant aspect in diminishing merged efficiency levels by means of a limited network span. What turns out to be different is the percentage of small aircraft, now positively affecting merged efficiency levels. These results suggest a beneficial impact of M&A in companies that operate small aircraft in terms of a more than proportional increase in the number of flights when compared to airlines where the fleet mix is concentrated on larger aircraft. This may not only be a result of an increase in actual flight demand, but also a consequence of feeding hub operations more intensely, as expected from airline mergers.

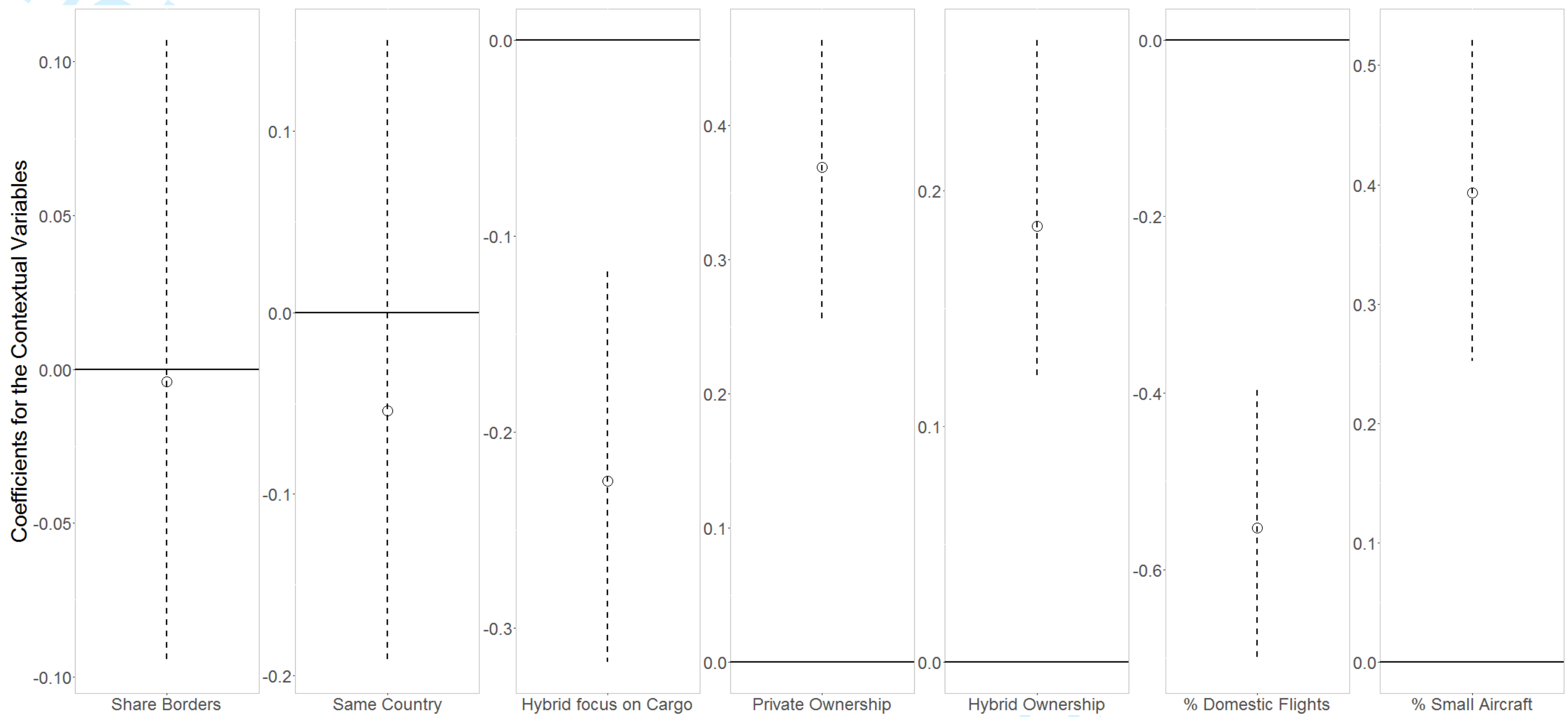

Fig 9 - Combined bootstrapped regression results for M&A efficiency scores in Latin American airlines

As regards RTS classification and prediction, results for the multinomial logistic regression are presented in Figs. 10 and 11, respectively. These results indicate the beneficial impacts of mergers in terms of a larger proportion of airlines operating at their most productive scale size (CRS) while lowering the proportion of companies that are too small or too big to face their actual needs in terms of the number of flights. Besides, only two contextual variables presented a significant result: “private ownership” and “hybrid ownership”. This suggests that a private administration in a merged airline is less likely to yield increasing returns-to-scale. In other words, the average pure public airline tends to be smaller than the average pure private or hybrid private one in Latin America. This also suggests that the role of the public sector within the ambit of the Latin American airline industry may be confined to small/underdeveloped market segments or niches, which are not so attractive to private players.

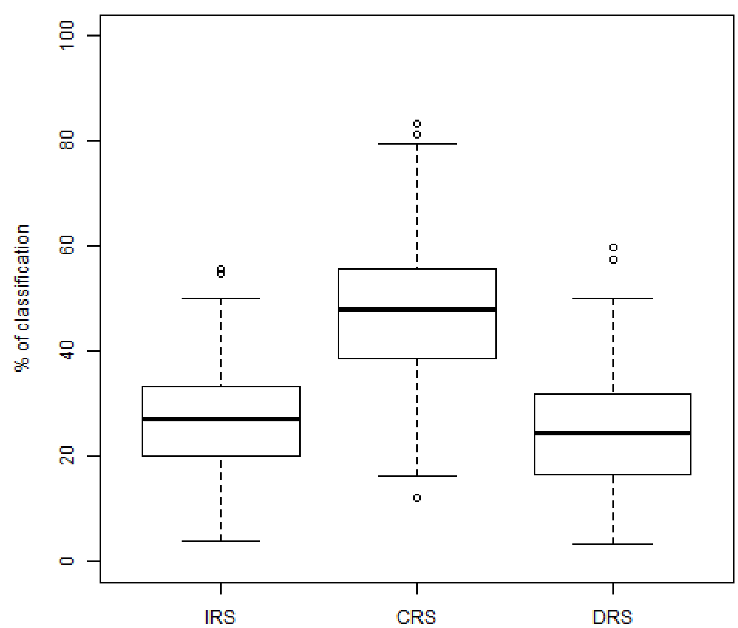

Fig 10 - RTS classification distribution of merged Latin American Airlines

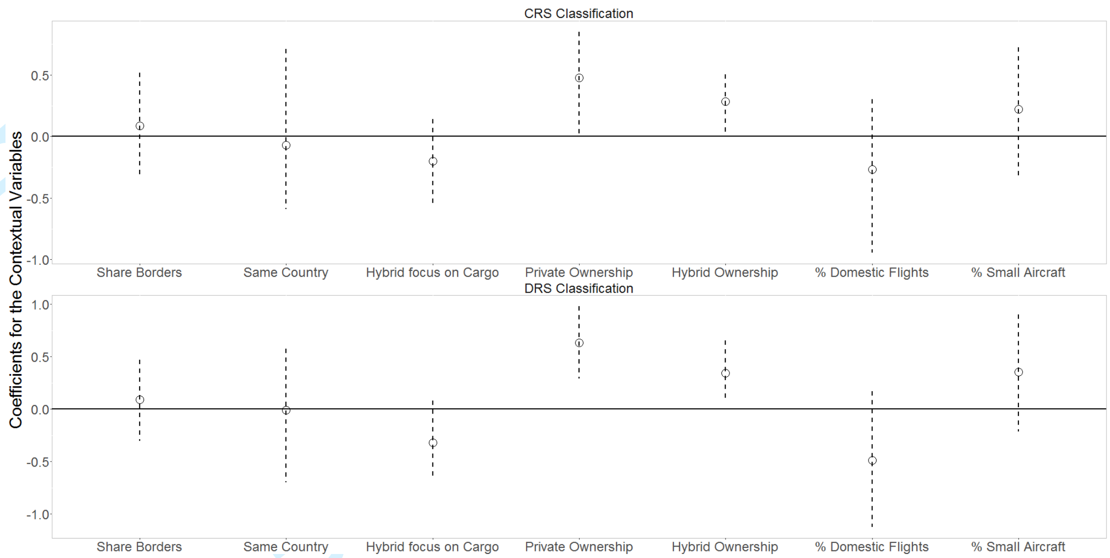

Fig 11 = M&A RTS prediction by bootstrapped multinomial logistic regression

7. Conclusion

This paper presents an analysis of the efficiency of Latin American airlines using the M&A DEA model and bootstrapped Robust/Multinomial logistic regression. M&A DEA enables the efficiency assessment of a virtual airline, thus enabling one to identify the optimal strategic fit between two possible companies to be merged. Based on the bootstrapped robust regression results, the drivers of virtual efficiency can be seen as fleet mix, ownership structure, and focus on passenger transportation. Through the analysis, the current study makes contributions from both the theoretical perspective and the practical perspective. First, the use of bootstrapped robust/multinominal logistic regression, compared to the methods adopted by the previous literature studies, generates more accurate and robust results related to the efficiency drivers due to its special feature and ability to allow the discrimination of increasing, decreasing, and constant returns to scale in light of a given set of contextual variables. From the practical perspective, the current study fills in the gap of the literature by clearly examining the pure effect of merging activity on efficiency gains. Fleet mix has shown some impact on virtual efficiency, meaning that operating smaller types of aircraft can represent demand opportunities for increasing the number of flights, possibly feeding hub networks or improving the number of movements, thus affecting their efficiency. Not only private ownership, but also a hybrid public-private ownership have a positive influence on virtual efficiency, suggesting an important governmental role in promoting M&A in the airline industry. Results also suggest that given the relatively small sizes of the markets in terms of the productive resources, M&A within Latin American airlines can be useful for achieving the most productive scale size, while experimenting with a slight increase on median efficiency levels. Further research is needed to confirm these results, especially with respect to those related to fleet mix and airline country of origin. Other regions around the globe should also be the object of future studies.

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Appendix

Table A1 - Results for the possible 171 mergers in 2014

Company.A	Company.B	M&A Efficiency (Model 2)	W (Model 2)	W* (Models 3 and 4)	APE W-W* (%)
Aerolineas Argentinas	Aeromar	0.950	3.847	3.903	1.42%
Aerolineas Argentinas	AeroMexico	1.000	7.839	7.894	0.70%
Aerolineas Argentinas	Avianca	0.883	8.209	8.265	0.67%
Aerolineas Argentinas	Avianca Brazil	0.790	3.808	3.863	1.44%
Aerolineas Argentinas	Bahamsair	0.964	2.864	7.448	61.54%
Aerolineas Argentinas	Boa - Boliviana de Aviacion	0.792	2.861	2.917	1.90%
Aerolineas Argentinas	Caribbean airlines	0.872	3.983	4.039	1.38%
Aerolineas Argentinas	Cayman airlines	0.834	2.416	2.472	2.25%
Aerolineas Argentinas	Copa airlines	1.000	7.462	7.518	0.74%
Aerolineas Argentinas	Cubana	1.000	8.800	8.812	0.14%
Aerolineas Argentinas	GOL	0.788	6.732	6.788	0.82%
Aerolineas Argentinas	InselAir	0.922	3.782	3.838	1.45%
Aerolineas Argentinas	Latam airlines group	1.000	9.408	26.490	64.48%
Aerolineas Argentinas	Liat	0.974	2.882	2.937	1.89%
Aerolineas Argentinas	Sky airways	0.846	2.723	2.779	2.00%
Aerolineas Argentinas	Surinam Airways	0.829	2.037	2.546	20.00%
Aerolineas Argentinas	TAME	1.000	3.193	3.249	1.71%
Aerolineas Argentinas	Volaris	1.000	6.515	6.570	0.85%

Aeromar	AeroMexico	1.000	8.168	8.205	0.46%
Aeromar	Avianca	0.928	8.150	8.206	0.68%
Aeromar	Avianca Brazil	0.722	4.273	4.604	7.19%
Aeromar	Bahamsair	1.000	3.603	9.478	61.99%
Aeromar	Boa - Boliviana de Aviacion	0.954	3.038	5.048	39.81%
Aeromar	Caribbean airlines	1.000	3.217	7.158	55.06%
Aeromar	Cayman airlines	1.000	2.798	5.431	48.48%
Aeromar	Copa airlines	1.000	8.161	10.167	19.72%
Aeromar	Cubana	1.000	5.500	10.717	48.68%
Aeromar	GOL	0.785	6.580	6.635	0.84%
Aeromar	InselAir	1.000	4.100	11.990	65.81%
Aeromar	Latam airlines group	1.000	9.741	9.779	0.38%
Aeromar	Liat	1.000	4.056	11.113	63.50%
Aeromar	Sky airways	0.876	3.825	3.952	3.21%
Aeromar	Surinam Airways	1.000	1.684	3.892	56.73%
Aeromar	TAME	1.000	4.547	5.893	22.85%
Aeromar	Volaris	1.000	5.935	8.308	28.57%
AeroMexico	Avianca	1.000	11.883	11.939	0.47%
AeroMexico	Avianca Brazil	0.989	7.790	7.846	0.71%
AeroMexico	Bahamsair	1.000	7.491	9.829	23.79%
AeroMexico	Boa Boliviana de Aviacion	0.993	7.054	7.109	0.78%
AeroMexico	Caribbean airlines	1.000	8.084	8.140	0.68%
AeroMexico	Cayman airlines	1.000	6.847	6.903	0.80%
AeroMexico	Copa airlines	1.000	11.594	11.631	0.32%
AeroMexico	Cubana	1.000	11.200	11.201	0.01%
AeroMexico	GOL	0.943	10.327	10.383	0.53%
AeroMexico	InselAir	1.000	8.039	8.077	0.47%
AeroMexico	Latam airlines group	1.000	14.021	14.059	0.27%
AeroMexico	Liat	1.000	7.538	7.576	0.50%
AeroMexico	Sky airways	1.000	7.099	7.155	0.78%
AeroMexico	Surinam Airways	1.000	3.850	3.863	0.35%

AeroMexico	TAME	1.000	7.854	7.892	0.48%
AeroMexico	Volaris	1.000	10.709	13.255	19.20%
Avianca	Avianca Brazil	0.827	7.929	7.985	0.70%
Avianca	Bahamsair	0.904	7.530	10.939	31.16%
Avianca	Boa Boliviana de Aviacion	0.805	7.148	7.204	0.77%
Avianca	Caribbean airlines	0.888	8.083	8.138	0.68%
Avianca	Cayman airlines	0.816	6.939	6.994	0.79%
Avianca	Copa airlines	1.000	11.620	11.676	0.48%
Avianca	Cubana	1.000	12.300	12.304	0.03%
Avianca	GOL	0.844	10.578	10.634	0.52%
Avianca	InselAir	0.910	8.017	8.072	0.69%
Avianca	Latam airlines group	1.000	14.700	34.454	57.33%
Avianca	Liat	0.911	7.592	7.647	0.73%
Avianca	Sky airways	0.832	7.225	7.281	0.76%
Avianca	Surinam Airways	0.807	4.098	4.112	0.32%
Avianca	TAME	0.941	7.895	7.950	0.70%
Avianca	Volaris	1.000	10.551	10.606	0.52%
Avianca Brazil	Bahamsair	0.715	3.588	4.317	16.88%
Avianca Brazil	Boa Boliviana de Aviacion	0.438	3.078	3.604	14.58%
Avianca Brazil	Caribbean airlines	0.593	4.123	4.304	4.21%
Avianca Brazil	Cayman airlines	0.480	2.901	3.504	17.19%
Avianca Brazil	Copa airlines	1.000	7.637	7.692	0.72%
Avianca Brazil	Cubana	1.000	5.700	5.704	0.07%
Avianca Brazil	GOL	0.687	6.373	6.429	0.86%
Avianca Brazil	InselAir	0.656	4.135	4.304	3.92%
Avianca Brazil	Latam airlines group	1.000	9.889	9.926	0.38%
Avianca Brazil	Liat	0.748	3.618	3.674	1.51%
Avianca Brazil	Sky airways	0.540	3.134	3.189	1.74%
Avianca Brazil	Surinam Airways	0.471	1.533	1.546	0.86%
Avianca Brazil	TAME	0.826	3.939	3.995	1.39%
Avianca Brazil	Volaris	1.000	6.877	7.791	11.73%

Bahamsair	Boa Boliviana de Aviacion	1.000	3.033	3.655	17.01%
Bahamsair	Caribbean airlines	1.000	3.216	6.010	46.48%
Bahamsair	Cayman airlines	1.000	2.905	3.922	25.94%
Bahamsair	Copa airlines	1.000	7.439	9.124	18.46%
Bahamsair	Cubana	1.000	5.200	5.229	0.56%
Bahamsair	GOL	0.753	5.984	8.632	30.68%
Bahamsair	InselAir	1.000	3.800	7.278	47.79%
Bahamsair	Latam airlines group	1.000	8.827	9.182	3.87%
Bahamsair	Liat	1.000	3.725	4.011	7.13%
Bahamsair	Sky airways	0.909	2.938	3.616	18.74%
Bahamsair	Surinam Airways	1.000	1.000	1.664	39.90%
Bahamsair	TAME	1.000	4.002	7.897	49.33%
Bahamsair	Volaris	1.000	5.921	8.081	26.73%
Boa - Boliviana de Aviacion	Caribbean airlines	0.775	2.684	5.030	46.65%
Boa - Boliviana de Aviacion	Cayman airlines	0.708	2.224	3.030	26.61%
Boa - Boliviana de Aviacion	Copa airlines	1.000	6.961	9.163	24.03%
Boa - Boliviana de Aviacion	Cubana	1.000	4.500	4.504	0.09%
Boa - Boliviana de Aviacion	GOL	0.637	5.589	5.645	0.98%
Boa - Boliviana de Aviacion	InselAir	1.000	3.100	5.763	46.21%
Boa - Boliviana de Aviacion	Latam airlines group	1.000	8.871	8.908	0.42%
Boa - Boliviana de Aviacion	Liat	0.933	3.157	3.372	6.36%
Boa - Boliviana de Aviacion	Sky airways	0.566	2.484	2.904	14.46%
Boa - Boliviana de Aviacion	Surinam Airways	0.699	1.158	1.929	39.99%
Boa - Boliviana de Aviacion	TAME	0.929	3.460	3.704	6.57%
Boa - Boliviana de Aviacion	Volaris	1.000	5.310	7.403	28.27%
Caribbean airlines	Cayman airlines	1.000	2.437	5.435	55.15%
Caribbean airlines	Copa airlines	1.000	8.066	9.871	18.29%

Caribbean airlines	Cubana	1.000	5.200	5.994	13.24%
Caribbean airlines	GOL	0.737	6.496	6.552	0.85%
Caribbean airlines	InselAir	1.000	3.800	8.571	55.66%
Caribbean airlines	Latam airlines group	1.000	9.945	9.983	0.38%
Caribbean airlines	Liat	1.000	3.652	5.385	32.19%
Caribbean airlines	Sky airways	0.740	3.548	4.008	11.46%
Caribbean airlines	Surinam Airways	1.000	1.526	3.880	60.66%
Caribbean airlines	TAME	1.000	4.139	5.359	22.76%
Caribbean airlines	Volaris	1.000	5.581	7.995	30.19%
Cayman airlines	Copa airlines	1.000	6.761	6.798	0.55%
Cayman airlines	Cubana	1.000	4.400	4.412	0.28%
Cayman airlines	GOL	0.644	5.392	5.447	1.02%
Cayman airlines	InselAir	1.000	1.000	1.000	0.00%
Cayman airlines	Latam airlines group	1.000	8.428	8.466	0.44%
Cayman airlines	Liat	1.000	2.987	3.205	6.80%
Cayman airlines	Sky airways	0.688	2.247	2.804	19.86%
Cayman airlines	Surinam Airways	1.000	1.000	1.340	25.37%
Cayman airlines	TAME	1.000	3.270	3.604	9.26%
Cayman airlines	Volaris	1.000	5.133	7.284	29.53%
Copa airlines	Cubana	1.000	10.500	10.603	0.97%
Copa airlines	GOL	1.000	10.061	10.117	0.55%
Copa airlines	InselAir	1.000	8.044	9.871	18.51%
Copa airlines	Latam airlines group	1.000	13.419	13.457	0.28%
Copa airlines	Liat	1.000	7.469	7.507	0.50%
Copa airlines	Sky airways	1.000	6.968	7.005	0.54%
Copa airlines	Surinam Airways	1.000	3.686	3.699	0.36%
Copa airlines	TAME	1.000	7.790	7.827	0.48%
Copa airlines	Volaris	1.000	10.782	12.572	14.24%
Cubana	GOL	0.882	10.000	10.004	0.04%
Cubana	InselAir	1.000	5.200	10.036	48.19%
Cubana	Latam airlines group	1.000	28.200	28.201	0.00%
Cubana	Liat	1.000	5.400	5.429	0.54%

Cubana	Sky airways	1.000	5.000	5.004	0.08%
Cubana	Surinam Airways	1.000	1.000	1.132	11.69%
Cubana	TAME	1.000	5.800	5.829	0.50%
Cubana	Volaris	1.000	7.900	8.694	9.13%
GOL	InselAir	0.759	6.439	6.494	0.86%
GOL	Latam airlines group	1.000	13.234	13.271	0.28%
GOL	Liat	0.765	6.049	6.105	0.91%
GOL	Sky airways	0.676	5.686	5.742	0.97%
GOL	Surinam Airways	0.633	3.163	3.176	0.42%
GOL	TAME	0.804	6.351	6.407	0.87%
GOL	Volaris	1.000	8.964	11.950	24.98%
InselAir	Latam airlines group	1.000	9.688	9.725	0.39%
Inselair	Liat	1.000	4.000	6.018	33.54%
InselAir	Sky airways	0.894	3.600	4.543	20.75%
InselAir	Surinam Airways	1.000	1.000	1.000	0.00%
InselAir	TAME	1.000	4.400	11.840	62.84%
InselAir	Volaris	1.000	6.500	8.227	20.99%
Latam airlines group	Liat	1.000	8.852	8.890	0.42%
Latam airlines group	Sky airways	1.000	8.734	8.772	0.43%
Latam airlines group	Surinam Airways	1.000	7.954	7.967	0.17%
Latam airlines group	TAME	1.000	9.133	9.170	0.41%
Latam airlines group	Volaris	1.000	12.246	12.301	0.45%
Liat	Sky airways	0.920	2.889	2.945	1.89%
Liat	Surinam Airways	1.000	1.482	1.495	0.89%
Liat	TAME	1.000	3.883	8.693	55.33%
Liat	Volaris	1.000	6.304	8.327	24.30%
Sky airways	Surinam Airways	0.680	1.172	1.185	1.12%
Sky airways	TAME	1.000	3.216	3.271	1.70%
Sky airways	Volaris	1.000	6.181	7.404	16.51%
Surinam Airways	TAME	1.000	1.651	1.664	0.80%
Surinam Airways	Volaris	1.000	2.947	5.692	48.22%
TAME	Volaris	1.000	6.777	8.737	22.43%

Table A2 - Spearman´s rank correlation matrix between the inputs and the output

	Total Flights	Employees	Number of Aircrafts
Total Flights	1.000		
Employees	0.579	1.000	
Number of Aircrafts	0.528	0.658	1.000

Table A3 - Results of the separability tests between output/inputs and contextual variables

Original DEA scores (N = 95)	0.075
M&A DEA scores (N = 855)	0.516

Table 1~~:~~.
Latin American airlines in 2014

Company	Country	Domestic flights	Latin American and Caribbean flights	World flights	Employees	Number of aircraft	Ownership	Year of Establishment
Aerolíneas Argentinas	Argentina	35	15	5	11,200	69	Public	1949
Aeromar	Mexico	20	0	2	900	19	Private	1987
Aeromexico	Mexico	44	13	22	13,000	122	Private	1934
Avianca	Colombia	42	32	16	19,650	170	Private	1919
Avianca Brazil	Brazil	24	0	0	4,032	40	Private	2008
Bahamasair	Bahamas-Nassau	13	2	4	641	9	Public	1973
BoA - Boliviana de Aviacion	Bolivia	7	3	2	978	14	Public	2007
Caribbean Airlines	Caribbean	2	11	6	1,000	23	Public	2006
Cayman Airways	Cayman Islands	2	4	5	386	6	Public	1968
Copa Airlines	Colombia	9	53	10	9,399	94	Public	1993
Cubana	Cuba	16	11	6	2,113	13	Public	1929
GOL	Brazil	52	13	2	16,157	140	Private	2001
InselAir	~~Aruba~~Curaçao	0	17	2	500	17	Public	2006
LATAM Airlines Group	South America	113	124	12	53,000	328	Private	2010
LIAT	Antigua	0	21	0	1,025	11	Private	1956
Sky Airline	Chile	13	4	0	1,800	16	Private	2002
Surinam Airways	Surinam	0	8	2	299	4	Public	1953
TAME	Ecuador	17	7	1	1,423	15	Public	1962
Volaris	Mexico	33	0	13	2,738	48	Private	2005

Table 2.~~:~~
Descriptive statistics for the inputs, output, and contextual variables

Variables			Min	Max	Mean	SD	CV
Inputs		Employees	266.00	53000.00	7020.76	11675.30	1.66
		Number of Aircrafts	4.00	328.00	60.38	79.23	1.31
Output		Total Flights	8.00	249.00	44.82	52.24	1.17
Contextual variables	Originals	% of Domestic Flights	0.00%	100.00%	48.37%	32.27%	0.67
		Large Aircrafts	0.00%	100.00%	65.28%	32.58%	0.50
		Small Aircrafts	0.00%	100.00%	28.47%	32.40%	1.14
		Cargo	Yes:	5.26%		No:	94.74%
		Public	Yes:	57.89%		No:	42.11%
Contextual variables	Secondary	% of Domestic Flights	0.00%	97.62%	50.49%	20.71%	0.41
		Large Aircrafts	0.00%	100.00%	69.23%	22.80%	0.33
		Small Aircrafts	0.00%	100.00%	26.67%	21.69%	0.81
		Share Borders	Yes:	9.94%		No:	90.06%
		Same Country	Yes:	3.51%		No:	96.49%
		Focus on Cargo	Strong:	0.00%	Weak:	10.53%	Inex: 89.47%
		Owner Structure	Public:	32.16%	Private:	16.37%	Hyb: 51.46%

Table 3.
KL divergence results for Beta, Simplex, and Gaussian assumptions

Simplex Fit	Beta Fit	Gaussian Fit
0.1095	0.0209	0.1128

Table 4.
KL divergence results for Beta, Simplex, and Gaussian assumptions

Simplex Fit	Beta Fit	Gaussian Fit
0.0775	0.0918	0.8565