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Efficiency in Latin American airlines: A two-stage approach combining Virtual Frontier Dynamic DEA and Simplex Regression

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ABSTRACT

This paper presents an efficiency assessment of Latin American airlines, using VDRAM-DEA (Virtual Frontier Dynamic Range Adjusted Model - Data Envelopment Analysis). In VDRAM, the reference and DMU evaluation sets are different, thus allowing higher discrimination of scoring. In this research, the VDRAM model is used first in a two-stage approach. In the second stage, Simplex Regression is adopted to handle skewed and asymmetrical efficiency scores. The results corroborate previous studies and reveal that the impact of fleet mix and public ownership cannot be overlooked in Latin American airlines, which seem to be affected by insufficient load factors and hub and spoke systems. For the same reasons, although low cost carriers are an emerging trend in the region, it was not possible to confirm their higher efficiency levels. Besides, to some extent, these findings also show the absence of a learning curve in Latin American airlines.

1. Introduction

This research focuses on the efficiency of Latin American airlines by using the VDRAM-DEA, presented in Li et al. (2016), as the cornerstone method to compute efficiency. Previous research on airlines has adopted several methods, such as the factor productivity approach (Bauer, 1990; Oum and Yu, 1995; Barbot et al., 2008); Stochastic Frontier Analysis or SFA (Good et al., 1993; Baltagi et al., 1995); the Turnquist total factor productivity index (Coelli et al., 2003; Barbot et al., 2008); and DEA (Data Envelopment Analysis) models (Merkert and Hensher, 2011; Barros et al., 2013; Barros and Peypoch, 2009; Barros and Couto, 2013). Papers have variously focused on 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), and African airlines (Barros and Wanke, 2015). Except for Melo Filho et al. (2014), who focused on wages in Brazilian airlines; and Oliveira and Huse (2009), who focused on Brazilian airlines' price reactions to market entry, thus far, to the best of our knowledge, few papers have focused on Latin American airlines. Therefore, this paper innovates by focusing on a comprehensive set of Latin American airlines.

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 – that is lower efficiency scores in contrast to traditional DEA models – when assessing, respectively, the efficiency of Asian and African airlines. Additionally, the authors advocate the combining of different predictive modelling techniques to explore effectively the impact of contextual variables on efficiency measurement. Therefore, this paper innovates in this context first by undertaking a review of Latin American airlines and, second, by adopting as a research tool the newly VDRAM, presented in Li et al. (2016), combined with Simplex Regression in a two-stage approach. To the best of our knowledge, this is the first time such approach is used to analyze airline efficiency in light of different contextual variables, simultaneously tackling two major problems in efficiency measurement: score discrimination and asymmetry.

The motivations for the present research follow. First, Latin America is one of the regions in the world most favored by the commodity price boom in the last ten years, with clear reflexes on airline traffic, justifying the present research. Second, this paper builds upon previous studies related to airline efficiency by

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evaluating relative efficiency among Latin American airlines. To the best of our knowledge, this is the first time Latin American airlines have been analyzed as a whole, thus differing from country-based level analysis. Third, the present analysis enables a ranking of the relative efficiency of the Latin American airlines using the newly developed VDRAM (Li et al., 2016), while assessing the impact of different contextual variables related to cargo type, ownership type, and fleet mix on their efficiency levels.

Therefore, the purpose of this study is to assess the determinants of airline efficiency in Latin America based on business related variables commonly found in the literature. In order to achieve this objective, an efficiency analysis is developed in a two-stage approach: VDRAM DEA model efficiency estimates are computed first, observing the prescriptions in Li et al. (2016), followed by Simplex regression. Researchers frequently face situations where they are interested in modelling proportions, percentages or values, such as efficiency scores, within the open interval (0; 1), according to one or several covariates, within the architecture of the regression. For this type of variable, the normal assumption is not supported, thus invalidating conclusions that might otherwise be obtained from these results. Asymmetry of the response variable and multicollinearity are two of the most frequent problems that the normal model cannot accommodate. In this situation, several alternatives have been developed, such as Beta regression, which leverages the advantages the general linear model, and simplex distribution, which is part of a more general class of models, i.e., dispersion models (López, 2013). The paper is structured as follows: after this introduction, the literature survey is presented. The methodology section, in which the two-stage VDRAM-Simplex regression is further discussed, follows next. Section 4 presents the data and the contextual setting, followed by the discussion of the results in Section 5 and the conclusions in Section 6.

2. Literature review

Research in airline frontier models encompasses several scientific methods to analyze efficiency quantitatively. First was the early tradition based on cost models (e.g., Caves et al., 1981, 1984; Windle, 1991; Baltagi et al., 1995; Oum and Yu, 1998; Liu and Lynk, 1999; Fritzsche et al., 2014). Second was the total factor productivity approach of Bauer (1990) adopted by Oum and Yu (1995) and Barbot et al. (2008). More recently, the contemporary stochastic econometric frontier models have gained popularity (e.g., Cornwell et al., 1990; Good et al., 1993; Sickles, 1985; Sickles et al., 1986; Captain and Sickles, 1997; Coelli et al., 1999; Inglada et al., 2006) and the DEA models (e.g., Distexhe and Perelman, 1994; Good et al., 1995; Adler and Golany, 2001; Fethi et al., 2001; Scheraga, 2004; Greer, 2008; Bhadra, 2009; Gitto and Mancuso, 2012).

Caves et al. (1981) assessed the productivity of eleven US airlines for the period 1972–1977. Caves et al. (1984) analyzed the impact of network size on the performance of US airlines. Caves et al. (1984) compared the productivity performance of a sample of US and non-US airlines over the period 1970–1983. Schmidt and Sickles (1984) analyzed the efficiency of US airlines. Gillen et al. (1990) compared the productivity of seven Canadian airlines over the period 1964–1981. Sickles (1985) analyzed the impact of deregulation on the performance of US airlines. Bauer (1990) assessed the efficiency and returns to scale of twelve US airlines over the period 1971–1981. Good et al. (1993) compared the performance of large European and US airlines over the period 1976–1986, and Oum and Yu (1995) compared the performance of European and US airlines over the period 1986–1993. Ehrlich et al. (1994) analyzed the impact of ownership on the productivity of European airlines. Captain and Sickles (1997) analyzed the impact of average stage length, network size, and percentage of the work force on the performance of European airlines. Coelli et al. (1999) analyzed the impact of stage length, load factor, and network size on the performance of US and European airlines.

Several issues have been addressed by these studies within these countries or regions. Besides, for example, rankings of efficiency and comparisons of slack, the impacts of network size, ownership, and regulatory measures on the performance of the airline industry have also been assessed, by incorporating contextual variables in a two-stage approach (Barros et al., 2013). Indeed, recent papers maintain this focus. For example, Barbot et al. (2008) compared the efficiency of US, European, and Asian airlines with a DEA model. Barros and Peypoch (2009) analyzed European airline efficiency with a DEA two-stage model, applying the results of Simar and Wilson (1998). Assaf and Josiassen (2012) analyzed the efficiency of European and US airlines with a Bayesian frontier model. Wanke et al. (2015) and Barros and Wanke (2015) introduced the use of TOPSIS in airline efficiency measurement by focusing on the Asian and African cases, respectively. It is interesting to note, however, that despite the emergence of the phenomenon of low cost airlines (Pearson et al., 2015 and Yu et al., 2016), this is still a relatively understudied topic under the lenses of operational efficiency between them and the traditional full services carriers.

A summary of the literature review is presented in Table 1, which enumerates the objects of analysis and the models used in each paper over the last three decades of studies on airline efficiency. This paper builds upon this body of knowledge not only by revisiting and confirming in a relatively unexplored geographic region several findings related to the contextual variables, but also by offering additional insights on new contextual variables and methodological approaches where the discriminatory power of the efficiency models and the asymmetry of their computed scores are handled simultaneously.

Additionally, taking a closer look within each paper, it is clear that the most common inputs are labor, capital, and materials or capacity, while the most frequent outputs encompass revenues, profits, movements, and passengers. Therefore, in this study, as the input, we use the number of employees, and, as the dynamic factor, the total number of aircraft. The outputs used involves the number of domestic, world, and Latin and Caribbean flights. Additionally, it appears that although there has been, thus far, only one application of virtual frontiers in the airline industry (Li et al., 2015), no paper has adopted simultaneously VDRAM DEA and Simplex regression in a two-stage approach. Furthermore, as an additional innovation of this paper, no earlier work has analyzed Latin American airlines in isolation.

3. Virtual Frontier Dynamic Range Adjusted Model (VDRAM)

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 multiples inputs and outputs (Wanke, 2012). Consider a set of n observations on the DMUs (Decision Making Units). Each observation, DMU_j $(j = 1, ..., n)$ uses m inputs x_{ij} $(i = 1, ..., m)$ to produce s outputs y_{rj} $(r = 1, ..., s)$. 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 envelopment modelling for the variable return-to-scale frontier types, where ε is a non-Archimedian element and s_i^- and s_r^+ account, respectively, for the input and output slack variables (Zhu, 2003; Bazargan and Vasigh, 2003).

Table 1
Literature review.

Author(s)	Sample size and focus	Method(s) used
Caves et al. (1981)	15 US airlines	Multilateral TFP index
Caves et al. (1984)	9 US airlines	Translog Cost Frontier
Schmidt and Sickles (1984)	Largest US airlines	Cobb-Douglas Production function
Bauer (1990)	7 Canadian airlines	Translog Cost Frontier
Gillen et al. (1990)	8 US airlines	Translog cost Regression
Cornwell et al. (1990)	14 US and 27 international airlines	Cobb-Douglas Production frontier
Windle (1991)	Largest US airlines	Multilateral TFP index and cost function
Windle (1991)	Largest US airlines	Multilateral TFP index and cost function
Good et al. (1993)	9 US, 15 European, and 9 Asian airlines	Cobb-Douglas production frontier
Distexhe and Perelman (1994)	US and European airlines	DEA-CCR and Malmquist index
Good et al. (1995)	US airlines	Cobb-Douglas production frontier and DEA-CCR
Baltagi et al. (1995)	8 US, 8 European, and 7 Asian	Translog Variable Cost Function
Oum and Yu (1995)	32 international airlines	Multilateral TFP Index
Coelli et al. (1999)	11 US airlines	Translog Production Frontier
Liu and Lynk (1999)	18 international airlines, 20 international airlines	Cobb-Douglas Cost; Malmquist productivity index
Inglada et al. (2006)	39 International airlines	DEA-BCC and TFP Index
Barbot et al. (2008)	14 US airlines	DEA-BCC and TFP Index
Greer (2008)	8 US airlines	DEA-CCR and Two Stage regression
Greer (2009)	29 European airlines	Malmquist index
Barros and Peypoch (2009)	12 US airlines	DEA-CCR and two Stage regression
Assaf (2009)	7 Canadian Airlines	Stochastic Production Bayesian Frontier
Ouellette et al. (2010)	50 largest airlines	Technical Efficiency and allocative Efficiency
Chow (2010)	Chinese airlines, 2003–2007	Efficiency analyzed with DEA and productivity analyzed with Malmquist index
Sjögren and Söderberg (2011)	18 major UK airlines	Input Distance Function
Merkert and Hensher (2011)	15 US airlines	DEA Two Stage
Barros and Couto (2013)	23 European airlines	Malmquist and Luenberger productivity measures
Bilotkach and Huschelrath (2012)	Airline alliances	Conceptual approach
Barros et al. (2013)	11 US airlines, 1998 to 2010	B-convex DEA model
Wu et al. (2013)	Chinese airlines, other Asian airlines, USA airlines and European airlines, 2006–2010	Efficiency with CCR and BCC DEA model and a second stage regression explaining efficiency.
Tavassoli et al. (2014)	Iranian airlines in 2010	SBM-NDEA model (Slacks based measure network data envelopment analysis)
Lee and Worthington (2014)	Several airlines, 1994–2011	DEA and SFA and second stage regression
Barros and Wanke (2015)	African airlines, 2010–2013	TOPSIS and neural networks in a two-stage approach
Li et al. (2015)	World airlines, 2008–2012	Virtual Frontier Network Slack Based Model
Wanke et al. (2015)	Asian airlines, 2006–2012	TOPSIS and Markov-Chain Monte Carlo GLM model

$$\begin{aligned}
&\max\phi-\varepsilon\left(\sum_{i=1}^{m}s_i^-+\sum_{r=1}^{s}s_r^+\right)\\
&s.t.\\
&\sum_{j=1}^{n}\lambda_j x_{ij}+s_i^-=x_{io},\ \forall i\\
&\sum_{j=1}^{n}\lambda_j y_{rj}-s_r^+=\phi y_{ro},\ \forall r\\
&\lambda_j\geq 0,\ \forall j\\
&\sum_{j=1}^{n}\lambda_j=1
\end{aligned}\tag{1}$$

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 allocation 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.

Since the units of the inputs and outputs do not affect the optimum solution in the Range Adjusted Measure (RAM) model (Aida et al., 1998), thus improving the discriminatory power of DEA, RAM is used here to evaluate airline efficiency when there is a large difference in size between inputs and outputs. The use of RAM within the context of DEA models was originally proposed by Aida et al. (1998) and Cooper et al. (1999) and has been widely applied to evaluate efficiency (Steinmann and Zweifel, 2001; Sueyoshi and Sekitani, 2007; Wang et al., 2013).

The basic RAM (range-adjusted measure) model is given below:

$$\theta=1-\max\frac{1}{M+N}\left(\sum_{m=1}^{M}\frac{s_{m0}^-}{R_m^-}+\sum_{n=1}^{N}\frac{s_{n0}^+}{R_n^+}\right)\tag{2}$$

$$\begin{aligned}
&s.t.\ \ x_{m0}=\sum_{k=1}^{K}\lambda_k x_{mk}+s_{m0}^-,\ m=1,2,\ldots,M\\
&y_{n0}=\sum_{k=1}^{K}\lambda_k y_{nk}-s_{n0}^+,\ n=1,2,\ldots,N\\
&\sum_{k=1}^{K}k=1\\
&\lambda_k,s_{m0}^-,s_{n0}^+\geq 0
\end{aligned}$$

where-
$R_m^- = \max_{k=1,2,\ldots,K}(x_{mk}) - \min_{k=1,2,\ldots,K}(x_{mk})$ and $R_n^+ = \max_{k=1,2,\ldots,K}(y_{nk}) - \min_{k=1,2,\ldots,K}(y_{nk})$ are the ranges of the inputs and outputs.

To measure the intertemporal efficiency change, many models have been proposed, such as the window analysis of Klopp (1985), the Malmquist index DEA model by Färe et al. (1994) and the dynamic DEA model by Färe and Grosskopf (1996) and Tone and Tsutsui (2010). Compared with the dynamic model, the other models do not explain the effect of carry-over activities between two consecutive terms and the connecting activities between terms are not accounted for explicitly (Tone and Tsutsui, 2010). In this research, we adopt the dynamic RAM model (DRAM) as presented in Li et al. (2016):

$$\rho^{overall} = 1 - \max\sum_{t=1}^{T} w^t \left(1 - \frac{1}{m+s+2r}\left(\sum_{i=1}^{m}\frac{s_{it}^-}{Rx_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt-1}^-}{Rz_{i0t-1}} + \sum_{i=1}^{s}\frac{s_{it}^+}{Ry_{i-t}} + \sum_{i=1}^{r}\frac{s_{ilt}^+}{Rz_{i0t}}\right)\right)$$

$$s.t.\begin{cases} x_{i0t} = \sum_{j=1}^{n} x_{ijt}\lambda_{jt} + s_{it}^- \quad i = 1,2,\ldots,m \quad t = 1,2,\ldots T \\ z_{i0t-1} = \sum_{j=1}^{n} z_{ijt-1}\lambda_{jt-1} + s_{ilt-1}^- \quad i = 1,2,\ldots,r \quad t = 1,\ldots T \\ y_{i0t} = \sum_{j=1}^{n} y_{ijt}\lambda_{jt} - s_{it}^+ \quad i = 1,2,\ldots,s \quad t = 1,2,\ldots T \\ z_{i0t} = \sum_{j=1}^{n} z_{ijt}\lambda_{jt} - s_{ilt}^+ \quad i = 1,2,\ldots,r \quad t = 1,2,\ldots T \\ \sum_{j=1}^{n} z_{ijt\ -1}\lambda_{jt-1} = \sum_{j=1}^{n} z_{ijt}\lambda_{jt} \quad \forall i, t = 1,2,\ldots T \\ \sum_{j=1}^{n}\lambda_{jt} = 1 \quad t = 1,2,\ldots,T \\ \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \end{cases} \tag{3}$$

where x_{ijt} indicates the i th input for DMU j at period t , y_{ijt} stands for the i th output for DMU j at period t , z_{ijt} denotes the i th dynamic factor for DMU j at period t . $s_{it}^-, s_{ilt\ -1}^-, s_{ilt}^+, s_{it}^+$ stand for the input excesses, dynamic factor excesses in input, dynamic factor shortfalls in output and the output shortfalls, respectively. $Rx = \max(x) - \min(x), Ry = \max(y) - \min(y)$ *and* $Rz = \max(z) - \min(z)$ are the ranges of the inputs, outputs and dynamic factors. The term efficiency of term t is given by:

$$\rho_t = 1 - \frac{1}{m+s+2r}\left(\sum_{i=1}^{m}\frac{s_{it}^-}{Rx_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt-1}^-}{Rz_{i0t-1}} + \sum_{i=1}^{s}\frac{s_{it}^+}{Ry_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt}^+}{Rz_{i0t}}\right) \tag{4}$$

However, in the dynamic RAM model above, each decision-making unit compares its production ability with the production ability of an optimal real frontier. When its result is 1, the DMU is technically efficient; otherwise, the DMU is technically inefficient. Therefore, the differences between efficient DMUs cannot be distinguished in such circumstances. To overcome this disadvantage, a Virtual Frontier Dynamic RAM was proposed based on the Virtual Frontier DEA in recent papers (Bian and Xu, 2013; Cui and Li, 2014, 2015a, 2015b; Li et al., 2015). Hence, the overall efficiency of Virtual Frontier Dynamic RAM model $\theta_{overall}$ is measured by:

$$\rho^{overall} = 1 - \max\sum_{t=1}^{r} w^t \left(1 - \frac{1}{m+s+2r}\left(\sum_{i=1}^{m}\frac{s_{it}^-}{Rx_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt-1}^-}{Rz_{i0t-1}} + \sum_{i=1}^{s}\frac{s_{it}^+}{Ry_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt}^+}{Rz_{i0t}}\right)\right)$$

$$s.t.\begin{cases} x_{i0t} = \sum_{j=1}^{n} xx_{ijt}\lambda_{jt} + s_{it}^- \quad i = 1,2,\ldots,m \quad t = 1,2,\ldots T \\ z_{i0t-1} = \sum_{j=1}^{n} zz_{ijt-1}\lambda_{jt-1} + s_{ilt-1}^- \quad i = 1,2,\ldots,r \quad t = 1,\ldots T \\ y_{i0t} = \sum_{j=1}^{n} yy_{ijt}\lambda_{jt} - s_{it}^+ \quad i = 1,2,\ldots,s \quad t = 1,2,\ldots T \\ z_{i0t} = \sum_{j=1}^{n} zz_{ijt}\lambda_{jt} - s_{ilt}^+ \quad i = 1,2,\ldots,r \quad t = 1,2,\ldots T \\ \sum_{j=1}^{n} zz_{ijt-1}\lambda_{jt-1} = \sum_{j=1}^{n} zz_{ijt}\lambda_{jt} \quad \forall i, t = 1,2,\ldots T \\ \sum_{j=1}^{n}\lambda_{jt} = 1 \quad t = 1,2,\ldots,T \\ \lambda \geq 0, \ s^- \geq 0, \ s^+ \geq 0 \end{cases} \tag{5}$$

where xx_{ijt} indicate the inputs for DMU j at period t in the frontier reference set, y_{ijt} stands for the outputs for DMU j at term t in the virtual frontier reference set, zz_{ijt} denotes the dynamic factors for DMU j at term t in the virtual frontier reference set. The term efficiency of term t is

$$\rho_t = 1 - \frac{1}{m+s+2r}\left(\sum_{i=1}^{m}\frac{s_{it}^-}{Rx_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt-1}^-}{Rz_{i0t-1}} + \sum_{i=1}^{s}\frac{s_{it}^+}{Ry_{i0t}} + \sum_{i=1}^{r}\frac{s_{ilt}^+}{Rz_{i0t}}\right) \tag{6}$$

In this model, the reference DMU set and the evaluated DMU set are two different sets; this offers the possibility of distinguishing between the efficient DMUs in the traditional dynamic RAM model. During the evaluating process, the reference DMU set remains unchanged so that its results may be more reasonable than existing models. The selection of the virtual frontier sets observes $x_{i0t} = \min_j\{x_{ijt}\}, y_{i0t} = \max_j\{y_{ijt}\}, j = 1,2,\ldots,n$ represents the DMUs, x_{ijt} denotes the inputs of DMU j at term, y_{ijt} denotes the outputs of DMU j at term t . According to the literature (Cui and Li, 2014, 2015a, 2015b; Li et al., 2015), for the virtual frontier reference set, the inputs are set as $xx_{ijt} = 0.95x_{i0t}$, the outputs are set as $yy_{ijt} = 1.05y_{i0t}$, and the dynamic factors are set as $zz = z$.

From the selection of the reference DMU set, it is expected that the inputs of reference DMU are less than the real DMUs and that the outputs are larger than the real DMUs. Therefore, the efficiency estimates of the Virtual Frontier Dynamic RAM are lower than those obtained from the traditional dynamic RAM model.

4. Data and efficiency prediction using Simplex Regression

4.1. 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 ALTA association includes airlines of almost all Latin American countries. Table 2 presents the airlines analyzed.

Table 2
The Latin American airlines in 2014.

Company	Country	Domestic flights	Latin American and Caribbean flights	World flights	Employees	Number of aircraft
Aerolíneas Argentinas	Argentina	35	15	5	11,200	69
Aeromar	Mexico	20	0	2	900	19
Aeromexico	Mexico	44	13	22	13,000	122
Avianca	Colombia	42	32	16	19,650	170
Avianca Brazil	Brazil	24	0	0	4032	40
Bahamasair	Bahamas-Nassau	13	2	4	641	9
BoA - Boliviana de Aviacion	Bolivia	7	3	2	978	14
Caribbean Airlines	Caribbean	2	11	6	1000	23
Cayman Airways	Cayman Islands	2	4	5	386	6
Copa Airlines	Colombia	9	53	10	9399	94
Cubana	Cuba	16	11	6	2113	13
GOL	Brazil	52	13	2	16,157	140
InselAir	Aruba	0	17	2	500	17
LATAM Airlines Group	South America	113	124	12	53,000	328
LIAT	Antigua	0	21	0	1025	11
Sky Airline	Chile	13	4	0	1800	16
Surinam Airways	Surinam	0	8	2	299	4
TAME	Ecuador	17	7	1	1423	15
Volaris	Mexico	33	0	13	2738	48

Table 2 shows that airlines from all major Latin American countries (Brazil, Mexico, Argentina, and Chile) are represented. Moreover, all major Latin American airlines are analyzed. 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 USA. Based at Mexico City International Airport, Aeromar is a private airline owned by Grupo Aeromar. 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 the second oldest airline, after the German KLM. Its hub is located in Bogota, Colombia. Avianca has several subsidiaries: Avianca-Brazil, Avianca-Costa Rica, Avianca-Equador, Avianca-El Salvador, Avianca-Peru, and Avianca-Cargo. The private company is 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 USA, 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 the 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 Aruba, 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 the 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 January 2007 this private airline merged with Caribbean Star Airlines. Chile's Santiago-based Sky Airline is also 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 established at the international airport at Quito. This airline was founded on December 1962. Volaris is a private Mexican airline located in Tijuana, Mexico. The second largest Mexican airline after Aeromexico, Volaris started ots low cost operations in 2005. The above airlines are representative of most Latin American countries.

The final sample size of 95 units involves the combination of 19 airlines for a period of five years. Inputs and outputs adopted in this research were in accordance with the literature review and data availability. As the single input, we used the number of employees; the total number of aircraft was the solely dynamic factor; and the outputs were represented by the total number of flights to Latin America and the Caribbean, to domestic destinations, and to the rest of the world. Their descriptive statistics are presented in Table 3.

In addition, six contextual variables were collected to explain the differences in efficiency levels. These are also presented in Table 3, and are related to the major business characteristics of the airline, namely: ownership type (whether public or not); whether the airline performs cargo transportation or not; and the fleet mix of the airline (percentage of large and small aircrafts). A dummy variable was also included with respect to the few existing low-cost airlines in Latin America: GOL (Brazil), Sky Airways (Chile), and Volaris (Mexico). Additionally, two contextual variables were used to represent the linear and squared components of an eventual learning curve.

Before proceeding, it is worthwhile presenting the grounds of the concept of dynamic factors and carry-overs in DEA in light of the variable selection depicted in the previous paragraph. In DEA, there are several methods for measuring efficiency change over time, e.g. the window analysis and the Malmquist index. However, they usually neglect carry-over variables between two consecutive terms. These carry-overs play an important role in measuring the efficiency of DMUs in each term as well as over the whole terms based on the long-term viewpoint. Dynamic DEA model proposed by Färe and Grosskopf (1996) is the first innovative contribution for such purpose. Then, Sengupta (1997) verified the dynamic efficiency embedded within the Farrell's productive structure (1957) – which ensembles the basic DEA models – while varying the capital input over the course of time. When presenting VDRAM application, also building upon the classic DEA models, Li et al. (2016) considered the capital stock as the dynamic factor or the carry-over effect to be used. According to Hill (1999), the capital stock, or simply capital, consists of all the fixed assets such as machinery, equipment, buildings and other structures used by enterprises to

Table 3
Descriptive statistics for the VDRAM and contextual variables.

Variables			Min	1st Qu.	Median	Mean	3rd Qu	Max.
Contextual and Business-related Characteristics	Learning curve	Trend	1.0000	2.0000	3.0000	3.0000	4.0000	2014
		Trend2	1.0000	4.0000	9.0000	11.0000	16.0000	5.0000
	Low-cost	Yes	0.0000	0.0000	0.0000	0.1579	0.0000	1.0000
	Cargo transportation	Yes	0.0000	0.0000	0.0000	0.05263	0.0000	25.000
	Ownership	Public	0.0000	0.0000	1.0000	0.5789	1.0000	1.0000
	Fleet mix	% Large Aircraft	0.0000	0.4375	0.7234	0.6528	1.0000	1.0000
		% Small Aircraft	0.0000	0.0000	0.2174	0.2847	0.5410	1.0000
VDRAM variables	Outputs	Number of Domestic Flights	0	2	15	22.38	33	113
		Number of Latin and Caribbean Flights	0	3	10	17.41	16	124
		Number of World Flights	0	1	3	5.032	6	22
	Input	Number of Employees	266	829	1607	7021	9701	53,000
	Dynamic factor	Number of aircraft	2	13	19	59.13	86.50	328

into processes of production. Therefore, in this research, the number of planes represents the productive resources accountable for the carry over effects in intertemporal efficiency levels, acting as mediators over the course of time between traditional inputs such as labors and outputs such as the number of destinations accomplished. It is also worth noting that dynamic efficiency models may also encompass productive network structures, where the outputs of the first stage consist of the inputs of the subsequent stage, which is not the case here since the single black-box approach is under consideration in the VDRAM DEA (Kawaguchi et al., 2014).

At last, some additional lines should be added with respect to zero-valued inputs and outputs in DEA. Following Barr (2004), these zero values were substituted by 0.01—according to the feature offered in different DEA softwares—in order to proceed with the analyses within the ambit of output-oriented models. Results found suggest that the methodological bias introduced by this procedure seems to be minimal, since the variation in efficiency scores were negligible. As a matter of fact, results presented in Section 6 still hold when 0.001 is used instead of 0.01.

4.2. Predicting efficiency levels using Simplex Regression

The Simplex regression has its roots in the Simplex distribution, which is a distribution that belongs to the family of dispersion models, with location and dispersion parameters μ and σ^2, respectively (also abbreviated as $DM(\mu,\sigma^2)$). The exponential dispersion family density (ED) has the form

$$p(y;\theta,\phi) = \exp\left\{\frac{y\theta - k(\theta)}{a(\theta)} + C(y,\phi)\right\}, y \in C \tag{7}$$

for some functions $a(\cdot)$, $k(\cdot)$ and $C(\cdot)$ with parameters $\theta \in \Theta$ and $\phi > 0$ and C is the support of the density. In particular, it is known that k is the cumulant generating function. Note that ED is the classical exponential family of the random component in the GLM framework.

The general form of a dispersion model is

$$p\left(y;\mu,\sigma^2\right) = a\left(y;\sigma^2\right) exp\left\{-\frac{1}{2\sigma^2} + d(y,\mu)\right\}, y \in C \tag{8}$$

where $\mu \in \Omega, \sigma > 0$ and $a \geq 0$ is a normalizer term, independent of μ.Function d is known as the *unit deviance* and is defined in $(y,\mu) \in (C,\Omega)$ and it must satisfy some additional properties (Song, 2007).

A simple advantage over the classical exponential family parametrization in (7) is that both, mean and dispersion parameters, μ and σ^2, are explicitly in the density expression (8) whereas in (1), $\mu = E(Y) = k'(\theta)$.

More precisely the parameter $\mu = E(Y)$ and $\mathrm{Var}(Y) = \frac{\sigma^2}{V(\mu)}$, where $V(\mu)$ is directly related with $d(\cdot;\cdot)$, i.e., $V(\mu) = \frac{2}{\left.\frac{\partial^2 d(y;\mu)}{\partial\mu^2}\right|_{y=\mu}}, \mu \in \Omega$ This function is known as the "unit variance function". Specifically, if y follows a simplex distribution, that is $y \sim S^-(\mu;\sigma^2)$, then (8) takes the form:

$$p\left(y;\mu,\sigma^2\right) = \left[2\pi\sigma^2\{y(1-y)\}^3\right]^{-\frac{1}{2}} \exp\left\{-\frac{1}{2\sigma^2}d(y;\mu)\right\}, y \in (0,1), \mu \in (0,1) \tag{9}$$

In particular, where

$$a\left(y;\sigma^2\right) = \left[2\pi\sigma^2\{y(1-y)\}^3\right]^{-\frac{1}{2}}$$

and

$$d(y;\mu) = \frac{(y-\mu)^2}{y(1-y)\mu^2(1-\mu)^2}, y \in (0,1), \mu \in (0,1)$$

it follows that $\mathrm{E}\{d(Y;\mu)\} = \sigma^2$, $\mathrm{E}\{d'(Y;\mu)\} = 0$, $\mathrm{Var}\{d(Y;\mu)\} = 2(\sigma^2)^2$. These and others features can be studied in detail at Song (2007). Other inferential properties can be studied in the seminal paper by Barndorff-Nielsen and Jørgensen (1991). The distribution can have one or two modes and can take the approximate shape of a bell, U, J, or L (also known as reverse-J) for different combinations of its parameters. It is important to note that the simplex distribution cannot emulate a flat distribution as the uniform distribution on the interval $(0,1)$.

Let be $Y_1,\ldots,Y_n$ independent random variables following the distribution in equation (9) with the mean μ_i and the dispersion parameterσ_i^2, and let be $\mathbf{x}_i = (x_{i1}, x_{i2}, \ldots, x_{ip})$ and $\mathbf{w}_i = (w_{i1}, w_{i2}, \ldots, w_{iq})$, $i = 1,\ldots,n$, vectors of covariate information. It is important to note that covariables $\mathbf{x}$ and $\mathbf{w}$ can be identical or they could be subsets of each other. We want to model the mean value μ_i and the dispersion parameter σ_i^2.

Similar to Cepeda and Gamerman (2001), Smithson and Verkuilen (2006) and Song et al. (2004), two link functions, g and h will be considered: one for each parameter in the simplex distribution. A convenient function g for the mean is the logit function, which ensures the parameter μ is in the open interval $(0,1)$. More specifically

$$g(\mu_i) = \log \frac{\mu_i}{1-\mu_i} = \mathbf{x}_{\boldsymbol{i}}^{\top} \boldsymbol{\beta} \tag{10}$$

where $\boldsymbol{\beta} = (\beta_0, \ldots, \beta_p)$ is a vector of unknown parameters. Equation (10) is also known as the location submodel.

The logit function has an extensive application in the field of statistics. This transformation helps to give answers in terms of the *odds ratio*. This is because the odds ratio between the predictive variable and its response variable can be found by using the relation $\mathrm{OR} = \exp(\beta_k), k = 1, \ldots, p$. On the other hand, the dispersion parameter σ_i^2 must be positive, and a function h that enjoys this property is the logarithm function. Therefore,

$$h\left(\sigma_i^2\right) = \log\left(\sigma_i^2\right) = \mathbf{w}_{\boldsymbol{i}}^{\top} \boldsymbol{\delta} \tag{11}$$

where $\boldsymbol{\delta} = (\delta_0, \ldots, \delta_q)$ is a vector of unknown parameters that must be estimated. The equation (5) is known as the dispersion submodel.

5. Results and discussion

The efficiency levels calculated for 19 selected Latin American airlines from 2010 to 2014, using the VDRAM approach and considering different grouping criteria, are given in Figs. 1 and 2. The full set of VDRAM scores is given in the Appendix. More precisely, in Fig. 1, VDRAM scores are disaggregated by year, and in Fig. 2, the scores are shown by year and country simultaneously, thus allowing for the analysis of each airline separately. It is worth noting that, although median efficiency levels are quite stable over the period analyzed (ranging around 0.75–0.82), substantial differences are apparent when efficiency levels are grouped by either countries or airlines. For instance, efficiency tends to decrease in smaller countries, such as Aruba, Cuba, and Cayman Islands – with the exception of Trinidad and Tobago, and remain stable or decrease in larger countries, such as Argentina, Brazil, Colombia, Mexico, and Chile. This suggests the presence of the eventual impact of contextual variables, which may be embedded within these groupings.

A robustness analysis was performed in order to compare the VDRAM scores with those computed from the traditional RAM (Aida et al., 1998) and DRAM (Li et al., 2016; Tone and Tsutsui, 2010) models (cf. Fig. 3). The major objective is not to only assess whether the VDRAM method increases the discriminatory power of the analysis against the efficient frontier, but also whether their scores are more symmetrical around the mean and, therefore, less biased towards 1.0.

The mean overall efficiency scores in the VDRAM method is 0.74, whereas the traditional DRAM and RAM models presented mean values of 0.78 and 0.87, respectively. This result suggests that the discriminatory power of the VDRAM method is higher than that observed in DRAM and RAM models, as their scores are lower and are not inflated towards one. The impact of VDRAM efficiency modelling can also be found in other statistical properties that are derived from the frequency distribution of efficiency estimates in both models. Although negative, that is, with a longer left tail and thus less concentrated around 1.0, VDRAM skewness is lower −1.06, against 0.087 [RAM] and −1.03 [DRAM], which suggests that, in the VDRAM method, efficiency scores are more asymmetrical around the mean, and that they not only favor the Simplex Regression analysis, but also other robust predictive modelling techniques. Nevertheless, Spearman rank correlation between efficiency scores derived from DRAM model and those derived from the VDRAM method were found to be extremely high (0.98) and significant at 0.01, thus suggesting isotonic results for both models.

Next, a Simplex regression analysis was performed on the VDRAM efficiency scores, using the contextual variables presented in Section 4.1 as their predictors. The coefficients and significance of each contextual variable are shown in Table 4. With regards to VDRAM efficiency scores, the significant predictors for the Latin American airlines are variables that are related to fleet mix (percentage of large aircrafts) and public ownership. The impact of trend is negligible.

Fleet mix presented a negative impact on levels of efficiency, in that smaller aircrafts, such as those manufactured by Embraer or Bombardier, are positively related to higher levels of efficiency, which is probably due to the smaller operating costs per aircraft. The bigger aircraft manufactured by Boeing, Airbus, and McDonnell-Douglas, all contributed to lowering levels of efficiency. This finding corroborates Barros and Wanke (2015) in the analysis of African airlines. The impact of fleet mix on levels of efficiency may depend upon the forces that drive economies of density and economies of scope for Latin American airlines. In the airline industry, in general, passenger-sensitive costs are small (e.g. food, ticket handling), in relation to flight-specific fixed costs. Thus, as traffic volume increases, an airline is able to fill a larger proportion of its seats on a given type of aircraft and thus increases its load

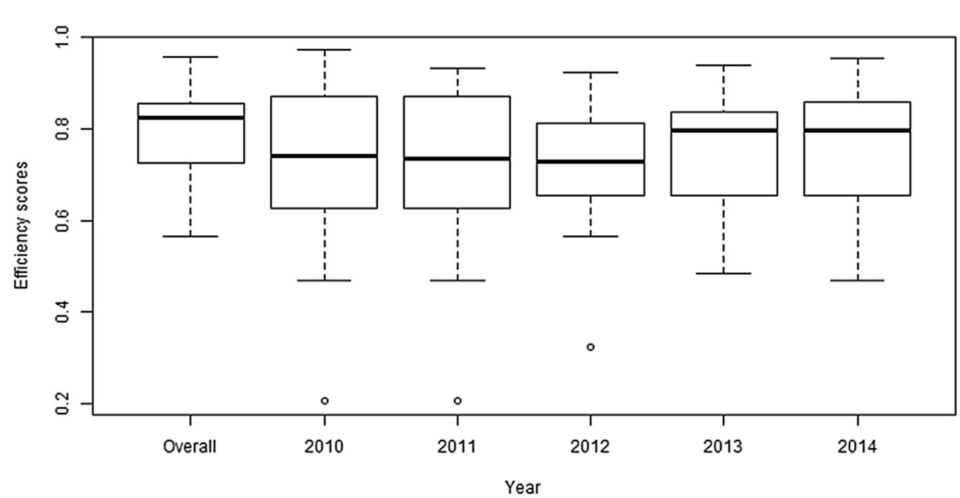

Fig. 1. VDRAM efficiency levels: overall and per year.

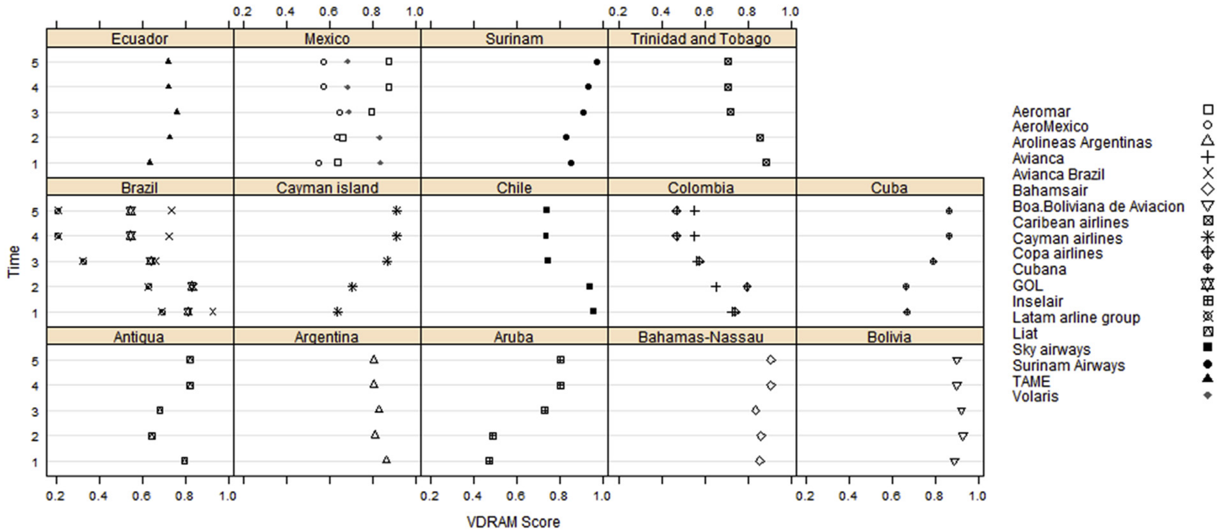

Fig. 2. VDRAM efficiency levels grouped by airline and by country (Time 1 = 2010 and Time 5 = 2014).

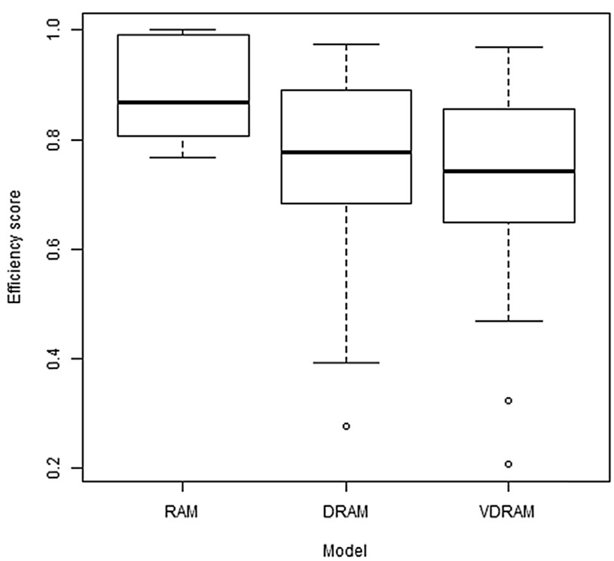

Fig. 3. Robustness analysis.

Table 4
Simplex regression results.

Coefficients	Estimate	Std. Error	z value	Pr(>|z|)
(Intercept)	1.61958	0.55408	2.923	0.00347**
Cargo operation	−0.33026	0.37690	−0.876	0.38090
Public ownership	0.42453	0.17371	2.444	0.01453*
% Large Aircrafts	−0.79474	0.40929	−1.942	0.05217.
% Small Aircrafts	−0.36288	0.41725	−0.870	0.38446
Low Cost	0.15924	0.22353	0.712	0.47622
Trend	−0.14687	0.28150	−0.522	0.60184
Trend^2	0.02071	0.04608	0.449	0.65309
Signif. codes: 0 '*' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1**				
Log-likelihood: 27.68, p-value: 0.4798351				
Deviance: 87				
Number of Fisher Scoring iterations: 18				
Standard Pearson residuals:				
Min	**1Q**	**Median**	**3Q**	**Max**
−2.6621	−0.4296	0.2266	0.6739	1.5333

factor; moreover, its costs per RPK fall as flight-specific fixed costs are spread over an increased volume in traffic. However, a key aspect in this analysis is the size of aircraft. According to Besanko et al. (2014), a larger aircraft (e.g., one with more than 300 seats) that is flown a given distance at a given load factor is less than twice as costly as a smaller aircraft (i.e., with 150 seats or less) flown the same distance at the same load factor. Putting this into perspective, and taking a less prescriptive view regarding the assumptions of Besanko et al. (2014), the results derived from this research suggest that load factors are low within the context of Latin American airlines and that they act as drivers in favor of operating with smaller aircraft. Several reasons may explain such lower load factors, from insufficient traffic density within a given route, to justifying operating with larger aircrafts, and even the scale of the network, which results in an insufficient hub and spoke system — probably a negative synergistic combination of both causes. Although it is expected that low cost carriers are more efficient that full service carriers – and this variable presented a positive sign in the case of Latin American airlines – it is interesting to note that these factors -insufficient hub and spoke system, scale of the network etc - may also be the underlying cause for the lack of significance of the low cost dummy variable.

Furthermore, public ownership is related to higher levels of efficiency, also corroborating Barros and Wanke (2015), and is probably due to the higher entrance barriers to launching an airline; indeed, in most Latin American countries, not only does a State monopoly prevail, flag carriers are also highly subsidized. Latin American countries tend to be middle-income and, as such, only the government has the capability of raising and/or mobilizing the funds or resources necessary for launching an airline. Lastly, the trend presented no impact on levels of efficiency, which suggests the absence of a learning curve in the case of the Latin American airline industry.

6. Conclusion

This paper presents an analysis of the efficiency of Latin American airlines, using VDRAM DEA modelling and Simplex regression. VDRAM makes it possible to rank airline efficiency, and it turns out there is much variation between airlines, with Sky Airline ranking first, with a score of 0.95 in 2010. Relative to the frontier of best practices, in which values equal to 1 signify full efficiency, this airline presents an inefficiency level of 1−0.95 = 0.05. The least efficient airline is LATAM, which scored 0.21 in 2014. Based on the Simplex regression results, drivers of efficiency are fleet mix and public ownership. Fleet mix has shown some impact on efficiency, meaning that operating certain types of aircraft can represent an additional cost to airlines, thus affecting their efficiency. Additionally, smaller aircraft, such as those manufactured by Embraer and Bombardier, have a positive impact on efficiency. Public ownership is also a positive influence on efficiency, which indicates that small markets are one of the major problems of Latin American airlines, which face tough regulation and enjoy public subsidies. This, however, maybe one of the major causes that helps in explaining why low cost airlines are as efficient as their full service counterparts are. With the exception of the learning curve, the airline market of Latin America resembles that of Africa with respect to economic fundamentals. Further research is necessary to confirm these results.

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Appendix. VDRAM scores

Year	Company	VDRAM term efficiency
2010	Sky Airline	0.95337
	Avianca Brazil	0.926288
	BoA - Boliviana de Aviacion	0.889837
	Caribbean Airlines	0.887132
	Aerolíneas Argentinas	0.860464
	Bahamasair	0.855011
	Surinam Airways	0.85118
	Volaris	0.835269
	GOL	0.810768
	LIAT	0.794028
	Copa Airlines	0.742582
	Avianca	0.727582
	LATAM Airlines Group	0.68941
	Cubana	0.669397
	Aeromar	0.638105
	TAME	0.634339
	Cayman Airways	0.634148
	Aeromexico	0.549989
	InselAir	0.470284
2011	Sky Airline	0.937598
	BoA - Boliviana de Aviacion	0.929263
	Bahamasair	0.860648
	Caribbean Airlines	0.85542
	Avianca Brazil	0.836453
	Volaris	0.832365
	GOL	0.829326
	Surinam Airways	0.828135
	Aerolíneas Argentinas	0.809306
	Copa Airlines	0.796662
	TAME	0.724628
	Cayman Airways	0.704478
	Cubana	0.663911
	Aeromar	0.657182
	Avianca	0.652429
	LIAT	0.641634
	Aeromexico	0.630977
	LATAM Airlines Group	0.627522
	InselAir	0.485633
2012	BoA - Boliviana de Aviacion	0.920247
	Surinam Airways	0.905916
	Cayman Airways	0.866409
	Bahamasair	0.836602
	Aerolíneas Argentinas	0.826573
	Aeromar	0.792882

(*continued*)

Year	Company	VDRAM term efficiency
	Cubana	0.792142
	TAME	0.760913
	Sky Airline	0.74585
	InselAir	0.727071
	Caribbean Airlines	0.721945
	Volaris	0.689349
	LIAT	0.680172
	Avianca Brazil	0.662588
	Aeromexico	0.646355
	GOL	0.638027
	Copa Airlines	0.574825
	Avianca	0.564086
	LATAM Airlines Group	0.323356
2013	Surinam Airways	0.931541
	Cayman Airways	0.9084
	Bahamasair	0.907354
	BoA - Boliviana de Aviacion	0.9003
	Aeromar	0.872806
	Cubana	0.864651
	LIAT	0.820501
	Aerolíneas Argentinas	0.804109
	InselAir	0.800466
	Sky Airline	0.73466
	Avianca Brazil	0.721828
	TAME	0.719272
	Caribbean Airlines	0.707014
	Volaris	0.682894
	Aeromexico	0.572503
	Avianca	0.552576
	GOL	0.544582
	Copa Airlines	0.468753
	LATAM Airlines Group	0.206976
2014	Surinam Airways	0.96964
	Cayman Airways	0.9084
	Bahamasair	0.907354
	BoA - Boliviana de Aviacion	0.9003
	Aeromar	0.872806
	Cubana	0.864651
	LIAT	0.820501
	Aerolíneas Argentinas	0.804109
	InselAir	0.800466
	Sky Airline	0.738752
	Avianca Brazil	0.733408
	TAME	0.719272
	Caribbean Airlines	0.707014
	Volaris	0.682894
	Aeromexico	0.572503
	Avianca	0.552576
	GOL	0.544582
	Copa Airlines	0.468753
	LATAM Airlines Group	0.206976

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