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Airline financial efficiency

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Abstract

This paper analyses the financial efficiency of airline companies by using third party capital to their financial returns and assets turnover. A previous work has determined three financial leverage intervals, classifying companies as great, fuzzy and bad, regarding their debt condition. A determinist model (Data Envelopment Analysis) to minimize indebtedness for a given return on assets, return on equity and assets turnover was the first step to rank companies. This technique resulted in a large fuzzy financial leverage interval for many companies. The use of two different non-deterministic methodologies, which were: neural network and decision tree, helped reduced this fuzzy area, allowing enhanced classification of companies. By combining a set of techniques, this study demonstrated how to reduce the number of company observations classified in the fuzzy area by nearly 84%. Therefore, this study provides a better reference to managers regarding their company's position in relation to their financial performance.

1 Introduction

Capital structure theory seeks to explain the motives that lead a company to choose a given financing structure for their business. A number of studies along these lines have identified several relevant factors, relating them to already developed lines of thought (Jensen and Meckling [1], Myers and Majluf [2], Harris and Raviv [3], Thies and Klock [4], Opler and Titman [5], Rajan and Zingales [6]).

Nonetheless, capital structure theory does not address what would be the optimal financial leveraging interval for companies. Determining a level suited to the business is of great importance to managers, since the choice of financing sources that comprise capital structure are related to profitability, tangible assets etc, in other words, to a set of factors that must be considered by the manager within the decision-making process. This article investigates the amount or amounts of indebtedness of the worldwide civil aviation industry, using the companies' financial results as a reference.

2 Data Envelopment Analysis (DEA) and Data Mining (DM)

Analysis of organizations' performance has been a keynote of the world globalization process. It is impossible to compete in this scenario without a continual quest for returns which are above average or even unequalled. This kind of higher performance can be attained by following paths which are quite different. This article combines three methodologies for performance analysis. DEA, Neural Network (NN) and Decision Tree (DT), the latter two being tools of DM.

2.1 Data envelopment analysis

Data envelopment analysis is a non-parametric method used for measuring the performance of a firm, organization or program i.e. whatever is produced by decision-making units (DMU). It includes a mathematical technique based on linear programming which does not need the functional form relating inputs to outputs to be specified. DEA optimizes each observation with a view to constructing an efficiency frontier (Figure 1). This consists of a discrete curve made up only of efficient DMU's. Obviously, we are dealing with relative efficiency as we are using samples. After determining the frontier we move on to the sample's benchmark for efficiency.

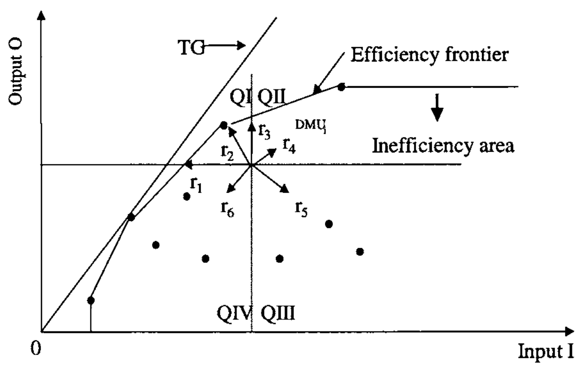

Figure 1: Data Envelopment Analysis and routes to improving performance.

Charnes et al. [7] proposed that DEA involves an alternative principle for extracting information about a group of observations. In contrast to the parametric approaches whose objective is to optimize a regression plan by data analysis, DEA optimizes every observation in order to calculate a frontier determined by Pareto-efficient DMU's. In this way DEA enables an efficiency analysis of each DMU and of possible ways of developing in the direction of the efficiency frontier (Figure 1).

Taking a DMU_i, ($i = 1 \ldots n$) as an example in Figure 1, it can be seen that an inefficient DMU can follow different development routes exemplified as r_1 to r_6. DEA mathematical models work, basically, with alternatives r_1, r_2 and r_3 which relate respectively to approaches oriented towards input, the shortest route to the frontier and output.

The main question in this study is with respect to the minimization of inputs that organizations are capable of (r_1). In this way an approach has been chosen which is input-oriented in a model with a variable revenue scale, as the article deals with organizations of different sizes. The convex shape of the efficiency frontier can be seen in the case we are analyzing. DMU's above the efficiency frontier with lower scale at the meeting of straight line TG with this frontier present returns growing in scale while those above represent returns diminishing in scale, as Banker et al. [8] explain.

2.2 Data mining

Neural Network is a methodology that offers the greatest amount of power in data mining. NNs attempt to build internal representations of models or patterns found in data, but that are not presented to the user. Through their use, the pattern discovery process is handled by DM programs within a "black box" process (Haykin [9], Hertz et al [10]).

Structurally speaking, a neural network consists of a number of interconnected elements (called neurons) organized in layers that learn by modification of the firm connection to the layers. Complex equational surfaces are generally built through repeated interactions, every hour adjusting the parameters that define the surface. After many repetitions, a surface may be internally defined that is quite close to the points within a data group.

The basic function of each neuron is: (a) evaluate input data, (b) calculate the error to combined input values, (c) compare the error to a threshold value, (d) determine the output. Neuron inputs are typically connected to an intermediate layer (or to several intermediate layers) that is connected to the output layer.

In order to construct a neural model, one must first train the network on a training dataset (data sample) and then use the trained network to make predictions. Sample design will depend on the type of data represented. (Kish [11])

Each neuron generally has a set of weights that determine how the neuron evaluates the combination of input signals. Each input can be either positive or negative to a neuron. Learning occurs through the modification of the weights used by the neuron according to the classification of errors made by the network as a whole. Inputs are generally weighted and normalized to produce a smooth procedure.

2.3 Decision tree

DTs are an evolution of the techniques that appeared during the development of the field of machine learning. They advanced from the approximation of an analysis called Automatic Interaction Detection, developed at the University of Michigan. This analysis works by automatically testing all values of a data to identify which ones are strongly associated to the output items selected for examination. Those values found to have a strong association are key prognostic values or explanatory factors, usually called data rules.

DTs are means of representing DM results in a tree-form, reminiscent of a horizontal organizational flowchart. Taking a group of data with several columns and lines, a decision tree tool asks the user to choose one of the columns as an output object and then displays the single and most important factor correlated to that output object as the first branch (node) of the decision tree. The remaining factors are subsequently classified as nodes of the former. This means that the user can quickly visualize which factor affects the output object the most, and the user is able to understand why this factor was chosen. A good DT tool will also enable the user to explore the decision tree at will, just as she or he may find target groups that are of greater interest, and thus expand the precise data associated to said target group. Users may also select the fundamental data in any node of the tree, moving it to within a spreadsheet or other tool for later analysis.

Decision trees are almost always used in conjunction with Rule Induction technology, yet are unique in the sense that they present the results of Rules Induction in a prioritized format. Thus, the most important rule is presented on the tree as the first node, and the less relevant rules are displayed as the subsequent nodes. The main advantages of decision trees are that they make decisions taking the most relevant rules into consideration, in addition to the fact that they are easier for most people to understand. By selecting and displaying the rules in order of importance, decision trees enable the users to see, at the time, what factors exerted the greatest influence in their work.

3 Data

In order to measure performance and capital structure with as undistorted a set of data as possible, we have used the corporate financial statement data compiled by Getting Results [12], Bridging the Gaap 3[13] and Bridging the Gaap 4 [14]. These data sets make a comparison possible between companies because they reflect adjustments made specifically for this purpose. Restating the financial reports of international airlines for purposes of comparability is important but not easy. The companies do not always closely follow the regulations for the publication of such reports. The information made available is determined by different countries' internal rules, so that it is difficult to construct an international sample. To the extent that they disclose the original accounting entries, it is possible to reconstruct the financial statements, using a single set of accounting principles. In general this requires both the adoption of International Accounting Standards as prescribed by the International Accounting Standards

Committee, and the standards that the International Air Transport Association (IATA) Accounting Policy Task Force have issued on specific topics affecting the airline industry. Difficulties in normalizing data consequently result in a reduction of available information and thereby limit the possibility of the choice of variables.

Rajan and Zingales [6] argued that several leverage measures exist, each adopting the one that best suits the purpose of their test. On the one hand, this causes problems in comparing different studies and makes theoretical generalization more difficult, yet on the other states the relation of variables through a number of measures. For example, Thies and Klock [4] tested five different categories. Although the authors found distinct values for each category, the results coincided in terms of the relation among the variables. In the case of this study, the total assets to equity were used to measure leverage. This is the measure of the shareholders' participation in the overall financing, or how much the shareholder believes in the business and is willing to invest. "This can be viewed as a proxy for what is left for shareholders in case of liquidation" (Rajan and Zingales [6]).

Considering the profitability variable, Rajan and Zingales [6] based their calculations by cash flow from operations normalized by the book value of assets. Two measures of profitability were used: net profit to total assets and net profit to equity. Our study added asset turnover, being understood that it is a measure of efficiency in the use of assets to generate revenue. These three measures were calculated at book value.

The sample is comprised of 50 companies from 29 countries, for the years from 1993 to 2000, in a total of 214 observations. We were not able to obtain observations for every year for all companies. We may cite as reasons for this, a change in the reporting period of financial statements of a given company (in this case we only accepted data with a regular interval of 12 months) and constraints of the DEA, which only accepts positive values other than zero.

4 Results analysis

Three leverage intervals described in Table 1 were identified in the study by Fernandes and Capobianco [15].

Table 1: Leverage intervals.

Intervals	Classification	Participation of shareholder capital in overall financing
From 1.3 to 2.5	Great	From 77 to 40%
From 2.6 to 4.2	Fuzzy	From 38 to 24%
Above 4.3	Bad	Below 23%

The efficiency frontier analysis shown on Table 2 indicates a level of 1.3 to 2.5 of leverage, where 97% of the references are concentrated. This result coincides with that obtained by Fernandes and Capobianco [15]. The other

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companies in the sample are considered inefficient in differing degrees. A path to improvement is indicated in each case. These indications are based on the performance observed in efficient companies. The frequency of indications is thereby formed and percentage of reference calculated. Frontier companies with the highest reference percentages are the sample benchmark. The others can be considered as special cases or test error percentage (3%).

Table 2: Efficiency frontier.

Reference	Frequency	(I)AF	(O)GA	(O)ROA	(O)RPL	Percentage of reference	
BRN94	138	1.9	2.16	0.078	0.152	30%	
TAM96	111	2.5	1.82	0.207	0.520	24%	
SIN94	96	1.3	0.54	0.076	0.102	21%	
SIN93	68	1.3	0.57	0.073	0.097	15%	
SIN95	38	1.3	0.52	0.077	0.105	8%	97%
TAM95	6	3.5	1.80	0.198	0.691	1%	
USA97	6	11.5	1.02	0.122	1.414	1%	
AIT00	2	68.3	1.14	0.086	5.875	0%	
BRN93	0	2.0	2.31	0.062	0.123	0%	
TAM93	0	6.1	2.28	0.066	0.401	0%	
TAM94	0	4.2	2.20	0.132	0.559	0%	

The companies were classified in binary form according to intervals obtained by Fernandes and Capobianco [15] and for the purpose of eliminating the fuzzy area: 1 for those with leverage of 1.3 to 2.5 and 0 for those with leverage above 2.6. Next, another classification was conducted from efficiency indices found by DEA: efficiency equal to or greater than 50% and efficiency lower than 50%.

Dividing the sample into two groups provides one group of 79 companies with an efficiency level equal to or greater than 50%. Table 3 shows the statistics from this sample.

Table 3: Statistics from sample with efficiency equal to or greater than 50%.

	(I)AF	(O)GA	(O)ROA	(O)RPL
Average	3.4	1.15	0.063	0.243
Standard deviation	7.5	0.50	0.037	0.669
Maximum	68.3	2.31	0.207	5.875
Minimum	1.3	0.42	0.001	0.003

Fifty-seven companies out of the total of this group had financial leverage of up to 2.5, that is, 72% of the sub-sample. Another 22 companies exist in this set with leverage greater than 2.5.

The second sub-sample contains 135 companies with an efficiency level below 50%. Table 4 shows the statistics from this group of companies.

Table 4: Statistics from sample with efficiency level below 50%.

	(I)AF	(O)GA	(O)ROA	(O)RPL
Average	7.6	0.86	0.031	0.228
Standard deviation	13.9	0.28	0.020	0.512
Maximum	128.4	1.74	0.093	5.551
Minimum	2.7	0.34	0.000	0.000

All of the companies of this total had a financial leverage above 2.5. There are 57 companies, however, within the fuzzy interval of 2.6 to 4.1. The remaining companies are in the area denominated as bad. Figure 2 summarizes the results.

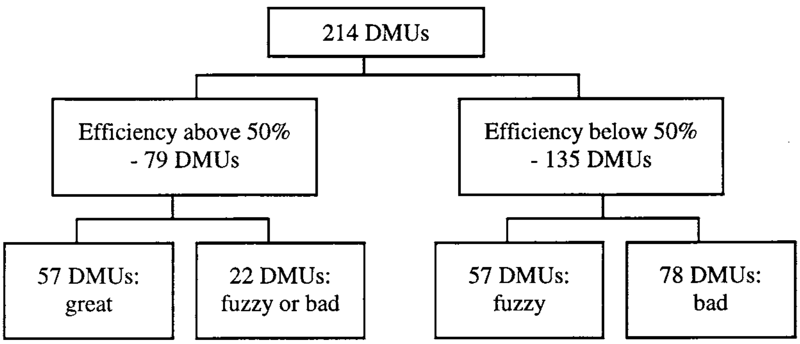

Figure 2: Results of company classifications.

Forty-five out of 50 companies (214 DMUs) possess observations from two years or more, totaling 209 observations. In analyzing the behavior of these 45 companies, we observed that 25 of them changed group, or 56%, which justifies the use of the different observations from each company and the analysis of the same company over different years in seeking best performance. Harris and Raviv [3] analyzed differences among industries and said that although they tend to maintain their leverage levels over time, relevant differences are found when analysis is conducted on a per company, per year basis. These changes are most likely the result of the macro and microeconomic environments in constant change that imposed alterations in the financial performance and leverage level of the companies.

Observe in Table 5 that there are no substantial differences between the percentage of observations among the four intervals in relation to G7 countries and the remaining countries in the sample. According to what was stated in the study by Harris and Raviv [3], the aviation companies in this sample possess a high level of leverage. Booth et al.[16], however, observed relevant differences between the leverage of companies in G7 countries and those from developing countries. According to these authors, companies in developing countries have

Table 5: Sample characteristics per interval.

Number of countries	Number of companies	Observations of Great interval (%)	Observations of fuzzy or bad interval (%)	Observations of fuzzy interval (%)	Observations of Bad interval (%)	Total number of observations	Average of observations per company
G7 – 6*	23	29	12	22	37	95	4,1
Other - 23**	27	24	9	30	36	119	4,4
All - 29	50	27	10	27	36	214	4,3

(*) G7 Countries within the sample: United States, Germany, Canada, Italy, Japan and the United Kingdom.
(**) 23 other countries within the sample: Australia, Austria, Bahrain, Belgium, Brazil, China, Singapore, Korea, United Arab Emirates, Spain, Finland, the Netherlands, Hong Kong, India, Ireland, Malaysia, Norway, New Zealand, Poland, Portugal, Sweden, Switzerland and Thailand.

lower leverage, regardless of the form of calculation, in terms of market or book value.

A NN and a DT were built so that their results could be compared to those from the DEA. The characteristics of the NN and of the DT are, respectively, the following: average error equal to 0.093381 with a learning rate of 0.15 and 0.8 momentum. The novel selection criteria were of the average error type and network architecture with a multilayer perception using a standard back propagation training technique. The following were model adjustment parameters for the DT: splitting criterion of the GINI reduction type, minimum number of observations two leaves; observation required for a split search 10; maximum numbers of branches from a node 4; maximum depth of tree 6 and splitting rules saved in each node 4. The 57 companies (Figure 2) of the great area and 77 of the 78 companies from the bad area were confirmed, while the ones from the fuzzy area can be repositioned through a comparison of the three tools. Sixty-six of the 79 companies in the fuzzy area migrated to the bad area, with one from the bad area migrating to the fuzzy area. Agreement amongst the results led to 84% of the total of 79 companies being defined, with only 16% of disagreement remaining amongst the three tools with relation to the classification of the companies. Table 6 summarizes the results.

Table 6: Results obtained through application of the DEA, neural network and decision tree.

	DEA		DEA/NN/DT	
	Number of companies	%	Number of companies	%
Great	57	27	57	27
Fuzzy	79	37	13	6
Bad	78	36	144	67
Total	214	100	214	100

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5 Conclusions

This study analyzed the efficiency of aviation companies in minimizing leverage given the indices of financial performance. The utilization of three analysis tools can classify the companies as possessing great and bad levels of leverage, considerably decreasing the number of companies within the fuzzy interval.

Utilization of neural networks and decision trees enable the identification of a clear trend that companies in the fuzzy area are most likely to provide poor financial performance. Confirmation of the group of companies on the efficiency frontier provides greater credibility to the results obtained in the DEA. Thus, it is clear that aviation companies that seek to position themselves amongst the best in the world in terms of financial results must pay close attention to their capital structure, as significant evidence exists that the same is related to said performance.

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