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AIRLINE DISTRESS PREDICTION USING NON-FINANCIAL INDICATORS

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ABSTRACT

When comparing the performance of airlines across countries, substantial differences are encountered in the financial environment that can be difficult to reconcile in the construction of a multi-country failure or distress prediction model. By using non-financial operating data and proxy variables for governmental influence and quality of economic environment, some of these problems are circumvented. Thus, in this study, a logistic regression model of airline distress prediction is constructed using three years of worldwide airline data [1996-1998]. The findings demonstrated a fairly good model, having 90.3 percent overall prediction accuracy. These findings in conjunction with other research in this field, support that models based on non-financial variables show good prediction traits comparable to financial based models, yet providing more explanatory power.

INTRODUCTION

Failure prediction models have been used extensively by the financial community for company evaluations and as early warnings systems of potential business failure (Theodossiou, 1991). Such models have been used by commercial banks and creditors to assess the creditworthiness of commercial users, by investors to measure a firm's risk of insolvency, and by business managers to assess and manage the financial turnaround of distressed companies.

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Four main approaches have been used in the development of prediction models: Univariate, Discriminant (multivariate), Conditional Probability and Neural Networks.[1] Let us cover each of these approaches briefly.

Beaver (1966) applied an univariate analysis (UVA) approach in which the predictive ability of the ratios was analyzed on a one-by-one basis. Beaver used seventy-nine industrial firms in his sample over a five year period. Each non-failed firm was matched with a failed firm by industry and asset size. The data analysis proceeded in three steps: a comparison of means, a dichotomous classification test, and an analysis of likelihood ratios. The comparison of means showed that the means of each ratio were significantly different for the failed and the non-failed firms. With the dichotomous classification, Beaver arrayed each ratio to a cut-off point. The best performing ratio was the ratio of *cash flow to total debt*, in that it showed the minimum percentage error in predicting the two groups in the sample studied.

Although Beaver's predictors perform fairly well, the main difficulty with his approach is that the classification can take place for only one ratio at a time. The potential exists for finding conflicting classification of any given firm according to various ratios. Altman (1968) argued that the financial status of a firm is actually multidimensional, and no single ratio is able to capture those dimensions; thus, a multivariate approach would be necessary to capture the dimensions. Consequently, the largest body of the academic failure prediction literature is applying discriminant analysis (DMA). DMA works in the way that a linear discriminant function is used to distinguish between distressed and non-distressed firms. The discriminant function transforms the values of the individual variables of the firm into a single discriminant score (z score), which is then used arbitrarily to classify the firms into the failed or non failed group (Frederikslust, 1978).

Altman used, in his pioneering DMA work, a sample of thirty-three manufacturers that filed for bankruptcy under Chapter X of the National Bankruptcy Act during the period 1946-1965. The accuracy of his model in the prediction of bankruptcy was 95 percent in the first year prior to bankruptcy and 72 percent in the second year prior to bankruptcy. In the third year prior to bankruptcy, the accuracy fell rapidly to 48 percent (see Table 10), or no better than a flip of a coin.

Most studies that followed attempted to improve the Beaver and Altman models in one way or another. Edmister (1972), for example, recognized that when many closely correlated variables are included, the resulting function is likely to be biased towards the sample from which it was developed. Thus, he eliminated highly correlated variables from the model. He also included in the study only those ratios that were found to be significant predictors of bankruptcy in previous empirical studies. The seven-variable discriminant function was accurate at an overall error rate of 7 percent in the first year prior.

At least two DMA studies have been applied to airline distress in the eighties (Altman and Gritta, 1984; Gritta, 1982): one specified a model, while the other applied the Altman Zeta model to the airline industry.

Other researchers have attempted to use different prediction techniques such as neural networks[2] and probability models. The conceptual basis of Neural Network (NN) models is rooted in attempts to simulate the neural construction of the human brain. One of the first applications of NN to failure prediction was by Tam and Kiang (1992), who specified models for bank failure. The models performed well one year and two years prior, but unlike most other prediction studies, no model testing was done on data three years or more prior to failure.

For predicting airline distress there have been two NN models, known to the author, one for major U.S. airlines (Davalos, Gritta, & Chow, 1999) and another for smaller carriers (Gritta, Wang, Davalos & Chow, 2000). Both of these models showed good prediction performance for the sample airlines one year prior to bankruptcy. The second model was not tested on two-year-prior or three-year-prior data for the same sample or a hold-out sample and cannot be fully compared with prediction models using other methodologies.

Although some methodological issues[3] are addressed with NN these models do not, so far, provide any break-through in prediction capability over MDA or Logistic Regression (LRA) approaches. For ease of comparability and interpetability, we selected the LRA methodology over NN for this study, which is a conditional probability approach.

Conditional probability models (Probit, Logit and LRA) are used to estimate the probability of occurrence of a choice or outcome. These models use the coefficients of the independent variables to predict the probability of occurrence of a dichotomous dependent variable. A cumulative probability distribution is needed in order to constrain the predicted values to comply with the limiting values (0, 1) of probability distributions. Some of the early applications of probabilistic methods in financial distress prediction are those of Ohlson (1980), Santomero and Vinso (1977) and Martin (1977).

Probability models are advantageous over discriminant models in that significant coefficients can be interpreted in terms of the relationship with the dependent variable and they are what is called distribution free methods, a considerable advantage over DMA. Ohlson (1980) argues, nevertheless, that certain discipline in data collection has to be adhered to. For example, the data has to be available prior to failure so that the model can be evaluated realistically. At least one study (Gudmundsson, 1999) has applied the LRA approach to airline distress, using a sample of new-entrant airlines in the U.S.A.

Performance Measurement of International Airlines

The airline industry, like many other industries, is increasingly exposed to competition. Increased competition has two effects on firms: it creates downward pressures on output prices, and it creates incentives for improving productivity and efficiency. Many airlines have been forced to undertake major restructuring in order to meet these challenges. Oum and Yu (1998) used a model to decompose changes in airline profitability into two components: productivity and price recovery ability. The study concluded that increased competition in international air transport markets has put pressures on carriers' ability to raise prices. However input prices, like labor, fuel, materials, flight equipment, ground property and equipment have been increasing. They also demonstrated that airlines have made tremendous effort to improve efficiency to counteract such trends, yet large fluctuations in profitability are still an ongoing reality.

Due to these fluctuations in airline fortunes, early warning systems of imminent distress are of benefit to management and airline stakeholders such as creditors and investors. No prediction model standardised on international airlines exists as far as the author is aware. One plausible reason is a problem in predicting distress of airline companies world-wide due to differences in economic and political systems. For example, in many countries there may be only one airline or few airlines making an industry-specific model for one country impossible to achieve. Thus, the main question in this research was if it would be possible to construct a prediction model that could be applied world-wide, taking into account differences in the political and economic environment of airlines.

Thus, given what we have covered so far, we construct a distress prediction model for international airlines based on non-financial data and pre-selection of input parameters. In the following section we will explain the conceptual framework (see Figure 1) that guided the selection of variables. Then the methodology is explained, followed by a report on the research findings.

CONCEPTUAL BACKGROUND

The conceptual framework used in this research to guide the selection of variables assumes that airline performance is a function of input resources and political and economic influences. Figure 1 shows the hypothesized relationship.

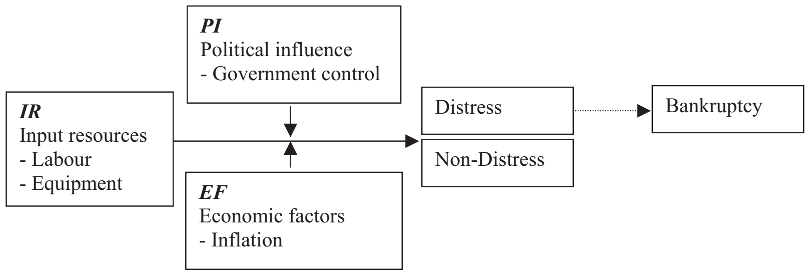


Figure 1. Relationship of factors used to predict airline distress

Input resources (IR) in airlines cluster around two main elements, namely labour and aircraft equipment, constituting the major part of the input costs in airlines. Poor management of equipment (fleet acquisition, composition and utilisation) and low labour productivity is assumed to be related to poor airline performance.

In general, newer aircraft are more efficient to run than older aircraft. Older planes have higher maintenance costs and fuel consumption. Thus, average fleet age should be a characteristic of poorer performing airlines. There can be two different reasons for this. First, the financial situation of the airline does not allow the acquisition or leasing of new equipment. Second, fleet acquisition and planning is poorly conducted due to inexperience or political influence. The last factor can play a role when political processes supersede airline operating interests in a market of substantial government influence (government airline or monopolistic market).

Since aircraft purchases take time (often two or three years), airlines should do some economic forecasting before going ahead with new aircraft orders to manage introduction in harmony with industry cycles. Poor fleet planning and aircraft acquisition policy can revert airlines to costly short-term solutions that fit poorly with the existing fleet composition. For example, by adding new poorly compatible brands[4] to the fleet raises costs due to increased crew costs and maintenance burden. Thus, it is assumed that airlines operating excessive number of aircraft brands will be poor performers.

The utilisation of aircraft, given the large associated cost and capital outlay, is of an outmost importance in airline management. Non-distressed carriers are expected to have higher number of departures per aircraft as a consequence of better overall management (schedules, distribution and marketing). An expected intervening factor is *average stage length*, that is a good performing carrier operating mostly long-distance routes should have *fewer departures per aircraft*. However, there was weak correlation between these two variables so regardless of long stage lengths non-distressed carriers may still achieve higher fleet utilisation measured as departures per aircraft than a comparable distressed carrier.

Size economies exist in the airline industry in terms of aircraft size. Meaning that the larger the aircraft the lower the operating cost per seat. Thus, the greater the average number of passengers carried per departure, a function of aircraft size and passenger load, the better the airline operating performance. This indicator was not significantly correlated with load-factor and thus a separate measurement in our conceptual model.

Another important input resource is people. Pilots are usually the most expensive labour resource. Hence, it is assumed that higher number of flight hours per pilot is related to better performing carriers.

Airlines are labour intensive and the *number of employees per aircraft* measures labour productivity, that is the fewer the employees per aircraft the higher the assumed labour productivity. Aircraft size could be an intervening factor, meaning that the larger the average fleet size the larger the number of employees per aircraft. To pre-test this hypotheses we correlated *average number of passengers per departure* with *employees per aircraft* and found non significant (r = 0.16) relationship. Thus, we conclude that *number of employees per aircraft* is a satisfactory general productivity measurement for our sample of international airlines.

Political influence (PI) is a factor in international air transport. Thus, impacting the management quality of airlines. In a bankruptcy prediction model we would expect proportionally high government ownership to work as a deterrent to bankruptcy that is to be linked to non-failure.[5] However, in a distress prediction model the assumption made was that the higher the proportional government ownership the less incentive there would be for an airline to pursue competitive cost structures and other efficiency measures. Thus, high proportional government ownership is linked with poorer performance and higher likelihood of distress status.

Economic factors (EF) were expected to play a role in the operating results of airlines. Inflation was selected as a proxy for quality of the domestic economic environment in which the airline operates. It is assumed that high inflation rates indicate poor unstable economic management having negative impact on airlines' operating results.

Following what has been covered so far it was expected that variables pertaining to these three areas of airline management (IR, PI, EF) should be good predictors of airline distress and non-distress status. The next part of the conceptual model deals with the dichtomous performance state of distress versus non-distress. Various definitions exist so we will discuss these in the context of our research.

One can argue that as long as a company is not dissolved or liquidated it must be seen as distressed, because a turnaround is still possible. According to Asquith (1991) financial distress can be associated with three main reason: an industry down turn, high interest expense, or poor firm operating performance relative to its industry. When is a firm financially distressed? *The Webster Dictionary* gives a general definition of distress as an acute financial hardship or being in great difficulty.

Altman (1993) distinguishes between technical insolvency and insolvency in a bankruptcy sense.[6] Technical insolvency is equal to the definition of financial distress. Altman defines the insolvency in a bankruptcy sense as a situation in which a firm's total liabilities exceed a fair valuation of its total assets. The two insolvency definitions do not lead to the same conclusion in all situations. A firm may have a negative economic net worth, but generate enough cash flow to escape bankruptcy (insolvent in a bankruptcy sense, but not technically). Or the other way around; cash flow is insufficient, but economic net worth is still positive (technically insolvent, but not in a bankruptcy sense).

Most prediction studies have relied on business closure, or sale, to trigger the classification of the business as either failed or non-failed. However, many businesses may continue operating even though they would be classified as having failed. In our research we assumed that bankruptcy is the total closure and liquidation of the firm following a period of distress. Thus, the focus is on predicting distress preceding bankruptcy rather than bankruptcy per se.

METHODOLOGY

In constructing a prediction model for the international airline industry we apply a non-financial approach to circumvent the problem of different accounting standards around the world. The airline industry is in many respects appropriate for non-financial approaches because of relatively homogenous sources of non-financial data available world wide through several statistical national and international programs: International Civil Aviation Organisation (ICAO), Association of European Airlines (AEA), and International Air Transport Association (IATA). Gudmundsson (1999) performed a comparison of various models constructed on data derived from a qualitative survey among airline managers and a quantitative data source containing traffic and financial data of new-entrant airlines. His main finding was that non-financial models performed better two and three years prior to distress than financial models, while the latter performed better one year prior. Based on the good performance of these prior models, we constructed a non-financial dataset for the international airline industry and applied the LRA approach to develop the prediction model.

The LRA Approach

Collins and Green (1982) find the LRA approach to have much more theoretical appeal to bankruptcy prediction, than Multiple Discriminant Analysis (MDA). One of the reasons, according to them, is that the logistic cumulative distribution function (Figure 2) is a sigmoid curve (*S*-curve) that has the threshold trait that the bankruptcy forecasting problem logically needs.

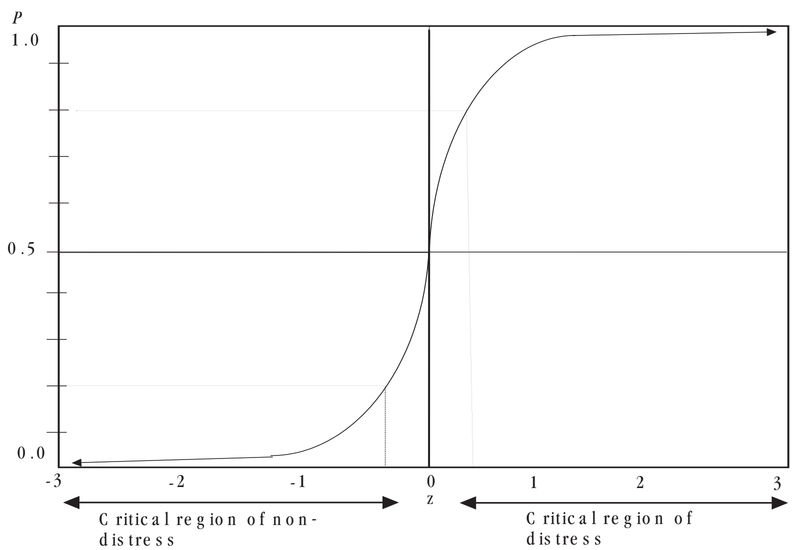


Figure 2. Sigmoid Probability Curve

We can see from Figure 2 that when the probability score falls along the lower bend of the curve (p = 0 to p = .2), the probability of failure is practically zero; however, if the score passes the bend and falls along the growth section of the curve (p = 0.2 to p = 0.5) the probability of failure increases dramatically. There is, however, little increase in the probability of failure as the change in the ratio falls along the upper bend of the curve (p = 0.8 to p = 1). Thus, the breaking point falls somewhere in the middle of the growth section of the curve (p 0.5) for example.

The logistic regression function produces a Z value that is transformed by the probability function into a probability. The Z is the linear combination of the resulting model. The function takes the form,

$$p(\text{failure}) = \frac{1}{1+e^{-z}}$$

where,

$$Z = B_0 + B_1 X_1 + B_2 X_2 + \ldots\ldots\ldots\ldots + B_p X_p$$

and

e = 2.718 (the base of the natural logarithms).

Data Description

The dataset used consists of ratios, as well as continuous and nominal variables collected over a period of three years (1996-1998) for 41 commercial airlines worldwide, covering economic, fleet, traffic and government equity in airlines.

The data was gathered from several sources. The primary sources were the *Air Transport World's* World Airline Report (1997, 1998, 1999) (government equity and fleet brands), *IATA World Airline Traffic Statistics* (1997, 1998, 1999) and *ICAO Annual Digest of Statistics: Series T and F* (1997, 1998, 1999).

Table 1 shows how the sample is spread geographically. Most airlines in the study are from Europe (39.0%), but fewest from Africa (4.9%) and Middle East (4.9%). Most distressed airlines come out of Europe (33.0%), as well as non-distressed airlines (43.0%).[7]

Table 1. Distressed and non-distressed airlines in sample by geographic location

Region	*Distressed*	*Non-distressed*	*Total*
Africa	2	0	2
Asia & Pacific	4	7	11
Europe	6	10	16
Latin America	4	2	6
Middle East	0	2	2
North America	2	2	4
	18	23	41

Table 2 shows the fleet size of the distressed (DA) and non-distressed (NDA) airlines. One can see that in the sample the non-distressed airlines have a larger fleet size than the distressed airlines in the categories 26-50 (NDA 33% vs. DA 20%) and 101-250 aircraft (NDA, 29% vs. DA, 10%), the distressed airlines have more frequency in the categories of less than 25 (NDA, 14.3% vs. DA, 20%) and 51-100 aircraft (NDA, 29% vs. DA, 40%).

Table 2. Fleet size of distressed and non-distressed airlines in sample

Fleet Size	*Non-distressed*	*Distressed*	*Total*
25 or less	3	4	7
26-50	7	4	11
51-100	6	8	14
101-250	6	2	8
More than 250	1	0	1
	23	18	41

The criteria applied to classify the airlines as either distressed (18 carriers) or non-distressed (23 carriers), was to look at the operating profit over a period. The operating profit and loss numbers were derived from the Airline Business (1997,1998,1999) and the *Air Transport World* (1997,1998,1999). An airline was classified as distressed, when it showed operating losses in the years 1997 and 1998, or when it had operating losses

Table 3. Airlines in sample, categorized as distressed and non-distressed

Distressed airlines (DA)	*Passengers*	*GEQ*	*Non-distressed airlines (NDA)*	*Passengers*	*GEQ*
Aerolineas Argentina	4,024,590	0	Aer Lingus	5,506,058	1
Air Afrique	995,620	1	Aeromexico	7,815,602	1
Air India	3,010,753	1	Air Canada	16,203,199	0
Canadian Airlines	8,168,862	0	Air China	6,453,623	1
Garuda Indonesia	6,623,472	1	Air Europe	2,564,591	0
Iberia	2,2259,083	1	Air France	33,497,633	1
Malaysian Airlines	13,654,438	0	Air Malta	1,159,398	1
Malev	1,749,232	0	Air New Zealand	6,426,013	0
Olympic Airways	6,403,393	1	Alaska Airlines	13,028,998	0
Philippine Airlines	7,405,147	0	All Nippon Airways	41,471,160	0
Sabena	8,748,544	0	Ansett Australia	11,970,225	0
South African Airw.	5,117,284	1	Austrian Airlines	3,234,190	1
Tarom	907,608	1	British Airways	36,592,684	0
Transbrasil	2,895,116	0	British Midland Airw	5,974,636	0
Turkish Airlines	9,949,301	1	China Southern Airli	14,455,242	1
TWA	23,909,333	0	El Al	2729022	0
Varig	11,214,963	0	Emirates	4,056,800	1
VASP	5,387,272	0	Finnair	6,771,138	1
			Japan Air System	19,518,067	0
			Korean Airlines	19,605,225	0
			Lan Chile	2,998,455	0
			SAS	21,506,858	1
			TAP Air Portugal	4,680,916	1
n = 18			*n* = 23		

GEQ = 1, government equity (equal to or greater than 25%); 0, no government equity. N = 41.

in three (or more) out of five years in the period 1994 until 1998. Since the purpose of the study is to segregate between the two performance states, this approach is more useful in identifying bona fide difference in the predictor variables.[8]

The Choice of Variables

In the research framework we used a number of ratios as well as other variables, continuous and nominal (Table 4). The reason for using ratios in a prediction model is to control for the effect of size on a dependent variable.

Table 4. Variables used in the model to predict airline distress

Variable	*Description*	*Type*
LF	load factor	Ratio
AVG.PASS	number of passengers carried per departure	Ratio
HRS.PILO	number of hours flown per pilot	Ratio
DEP.FLTS	number of departures per aircraft	Ratio
PLT.FLTS	number of pilots per aircraft	Ratio
EMP.FLTS	number of employees per aircraft	Ratio
AVG.AGE	average age of the aircraft fleet	Continuous
INFLATIO	annual inflation in the economy	Continuous
AC_BRANDS	number of different brands of aircraft operated	Continuous
GOVERM	political influence 1= yes, 0 = no.	Nominal

There is no generally accepted theoretical base on picking or selecting variables for prediction models, so an exploratory stance has usually been taken. In this study, however, a framework model guided the selection of variables.

As discussed earlier a study by Oum and Yu (1997) guided the selection of variables pertaining to input, while other variables were selected to fit into the prior conceptual model. At the beginning several ratios and variables were included for each of the categories as seen in Figure 1, but correlation analysis was used to eliminate highly correlated variables within each category. A condition of at least one variable in each category was set a priori.[9] We will now cover each of the variables in the model.

Variable Descriptions

Tables 5 and 6 give a detailed statistical description of each of the variables. Table 5 shows the means analysis and table 6 the correlations. The first variable is the *load factor* (LF), which is the degree of occupancy of an aircraft. It is calculated, as the number of seats sold divided by the number of seats available or more specifically revenue passenger kilometers divided by available seat kilometers. *Number of passenger* *carried per departure* (AVG.PASS), indicates average equipment size as well as load efficiency. The next variable (HRS.PILO) depicts the *number of hours flown per pilot*. The following variable (DEP.FLTS) measures the *number of departures per aircraft*. This ratio measures both route structure characteristics (short-haul, long-haul) and effective utilization of aircraft. The next ratio measures the *number of employees per aircraft* (EMPL.FLTS). The ratio is also a labor efficiency ratio and measures the number of employees in all employment categories per aircraft. The following variable is continuous and measures the *average age of the aircraft fleet* (AVG.AGE) employed. *Annual inflation* (INLATIO) is a continuous variable for each airline's national inflation level. The next variable is an indicator variable that depicts domestic *political influence* (GOVERM) on the airline through controlling stake (25% or more) or full ownership of the respective government. The final variable (is continuous and depicts the *number of different brands of aircraft operated* (AC_BRANDS) by each airline.

A t-test (Table 5) revealed three variables (LF, AVG.AGE, INFLATIO) having statistically significant difference between distressed and non-distressed airlines. This finding however does not necessarily mean that these ratios are significant predictor coefficients alone in a prediction model—as pointed out by Altman (1968).

Table 5. Significant differences between distressed and non-distressed airlines in sample

NDA = 23, DA = 18	*STATUS*	*Mean*	*S.D.*	*S.E. Mean*	*t-test*	*sig.of diff.*
LF	Non-distressed	67	4.80	1.00	2.01	0.045
	Distresseded	64	4.57	1.08		
AVG.PASS	Non-distressed	93.72	34.08	7.11	1.46	0.152
	Distressed	80.18	22.02	5.19		
HRS.PILO	Non-distressed	257.83	43.25	9.02	-0.86	0.394
	Distressed	27512	83.08	19.59		
DEP.FLTS	Non-distressed	1657.50	702.77	146.54	0.89	0.381
	Distressed	1484.26	496.65	117.06		
EMP.FLTS	Non-distressed	161.63	57.53	11.99	-1.63	0.111
	Distressed	211.93	133.02	31.35		
AVG.AGE	Non-distressed	9.40	2.75	0.57	-3.66	0.001
	Distressed	13.29	4.03	0.95		
INFLATIO	Non-distressed	3.02	3.84	0.80	-2.31	0.025
	Distressed	14.57	23.45	5.53		
AC_BRANDS	Non-distressed	3.17	1.80	0.38	-0.99	0.922
	Distressed	3.22	1.17	0.27		
GOVERM	Non-distressed	0.48	0.51	0.11	0.21	0.835
	Distressed	044	0.51	0.13		

Correlations

Table 6 shows the correlations of 8 of 10 variables included in the model. To test for collinearity both the TOLERANCE and the Variance Inflation Factor (VIF) was calculated. Variables under consideration were eliminated from the dataset if they posed a problem according to these tests. The TOLERANCE ranged from 0.79 to 0.89 and the VIF from 1.13 to 1.30. Thus, it was safely concluded that collinearity did not pose a problem in the eventual variable set.

FINDINGS

Table 7 shows the resulting model. As the model was constructed on predetermined framework that guided variable selection, all variables entered the model without any forward or backward elimination allowed.[10] Four variables had negative signs: load factor (LF), government equity (GOV_EQ), average number of passengers per departure (AVG.PASS) and departures per aircraft (DEP.FLTS). Negative sign indicates that the average mean is higher for the NDA carriers. However, only two coefficients were significant in the model so the relationships are only indicative for other variables. Although, insignificant, one would expect that high load factor, controlling government stake, more departures per aircraft and high average number of passengers carried per departure are positively related with non-distress.

The variables that appear associated with distress are also in accordance with expected direction of the relationship with the exception of flight hours per pilot. Airlines operating many brand types of aircraft, older fleets and in an unstable economy (high inflation) can be expected to be more prone to be distressed. However, flight hours per pilot was expected to be lower for distressed carriers. Means analysis, however, revealed non-significant difference between the two groups (NDA = 257.83 hours vs. DA 275.12 hours; p = 0.394). Yet this variable in combination with other variables was an effective predictor of the dichotomous dependent variable. This ratio had a weak negative correlation with average number of passengers per departure (r = 0.174). This could indicate that distressed carriers have on the average fewer departures per aircraft but more flight hours per pilot. Which could indicate higher average stage lengths, although our data did not reveal a significant difference in stage length between the two groups (NDA = 1357 vs. DA = 1401; p = 0.80). The same applied to average passenger haul (average km each passenger was carried). Although, this distance was higher on the average for distressed carriers the difference was non significant for the two groups (NDA = 1885 vs. DA = 2200; p = 0.24).

Table 6. Correlations between variables used to predict airline distress

	INFLATIO	*AC_BRANDS*	*-.008*	*AVG.PASS*	*EMP.FLTS*	*AVG.AGE*	*HRS.PILO*	*GOVERM*
LF	-.313*	-.069						
AVG.PASS	.007	.032	.174					
HRS.PILO	-.156	-.068	.149	-.174	-.071	.203		
DEP.FLTS	-.066	-.258	-.035	-.398**	.017	-.057	.220	-.188
EMP.FLTS	.230	-.065	-.007	.162				
AVG.AGE	-.014	-.168	-.121	-.310*	.036			
AC_BRANDS	.027							
GOVERM	.320*	.171	-.008	.020	.299	-.048	-.147	

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

Two coefficients were significant in the model: average age of fleet (AVG.AGE) ($p < 0.043$) and number of employees per aircraft (EMP.FLTS) ($p < 0.068$). As to the accuracy of the prediction model, non-significant coefficients do not pose a problem. However, lack of significance does limit interpretability of a coefficient in a LRA model. For prediction models, it is well established, that variables poor in distinguishing between distressed and non-distressed firms alone can in combination with other variables be effective in doing so (Zavgren, 1983).

Table 7. Airline distress prediction model

	B	*S.E.*	*Wald*	*Sign.*
LF	-.329	.217	2.297	.130
AVG.PASS	-.052	.047	1.248	.264
HRS.PILO	.016	.016	1.049	.306
DEP.FLTS	-.002	.002	1.787	.181
EMP.FLTS	.047?	.026	3.324	.068*
AVG.AGE	.685	.338	4.110	.043*
INFLATIO	.157	.113	1.922	.166
AC_BRANDS	.651	.538	1.464	.226
GOV_ERM	-1.518	1.201	1.597	.206
Constant	6.757	8.807	.589	.443

*statistically significant

The model summary statistics in Table 8 allow us to reject the null hypotheses that the independent variables are not related to the dependent variable. Furthermore, the level of association of the COX & SNELL R Square (0.559) and NAGELKERKE R Square (0.749) demonstrate good association between the independent variables and the dependent variable.

Table 8. Summary of airline distress prediction model

-2 Log likelihood	*Cox & Snell R Square*	*Nagelkerke R Square*
22.663	0.559	0.749

Table 9 shows the predictive power of the model. In each category there were two misclassified cases leading to 91.3 percent accuracy for the NDA group and 88.9 percent for the DA group. Overall accuracy of the model was 90.2 percent, which must be considered a good result compared to traditional benchmark models and airline industry specific prediction models (Table 10).

Table 9. Predictive power of airline distress prediction model

		Predicted STATUS		*Percentage Correct*
		Non-distressed	Distressed	
Observed STATUS	Non-distressed	21	2	91.3
	Distressed	2	16	88.9
				Overall 90.2

The cut value is 0.50.

Figure 3 shows the observed and predicted probabilities of each of the cases. Substantial number of the case probabilities fall into the extreme left ($p = 0.0$ to $p = 0.1$) and right ($p = 0.9$ to $p = 1.0$), which is a good trait of the model. A number of misclassified cases are near to the cut-off value ($p = 0.5$) showing borderline traits such as low profits but characteristic of a distressed carrier or vice versa.

LIMITATIONS

Perfect prediction capability of a model is unattainable for the reason of borderline cases, that is carriers shifting from a non-distress state to a distress state and vice versa, showing the characteristics of one over the other in the short- to medium-term. There are also other biasing factors such as creative adjustment of the numbers making the sample data non-reflective of the actual state of some firms. Given adequate sample size this problem is kept to a minimum, but can never be totally eliminated. Thus, some misclassification should always be expected.

There are some practical problems associated with prediction models. The most important problem is in the strict industry requirement, which is embodied in the methodology. Using such a model across a wide range of industries can be compared with the traditional custom of using the same benchmark for a current ratios across a wide range of industries: common but not a good practice. Our study meets this requirement by focusing on the airline industry.

Furthermore, usually the ratios contained in a model are determined at the time the model is developed. Thus, changing the specification of a ratio requires a complete re-evaluation of the model, as none of the ratios can be considered in isolation from the others. Any change to a single ratio has repercussions on the whole model. Yet, in our study we specified a

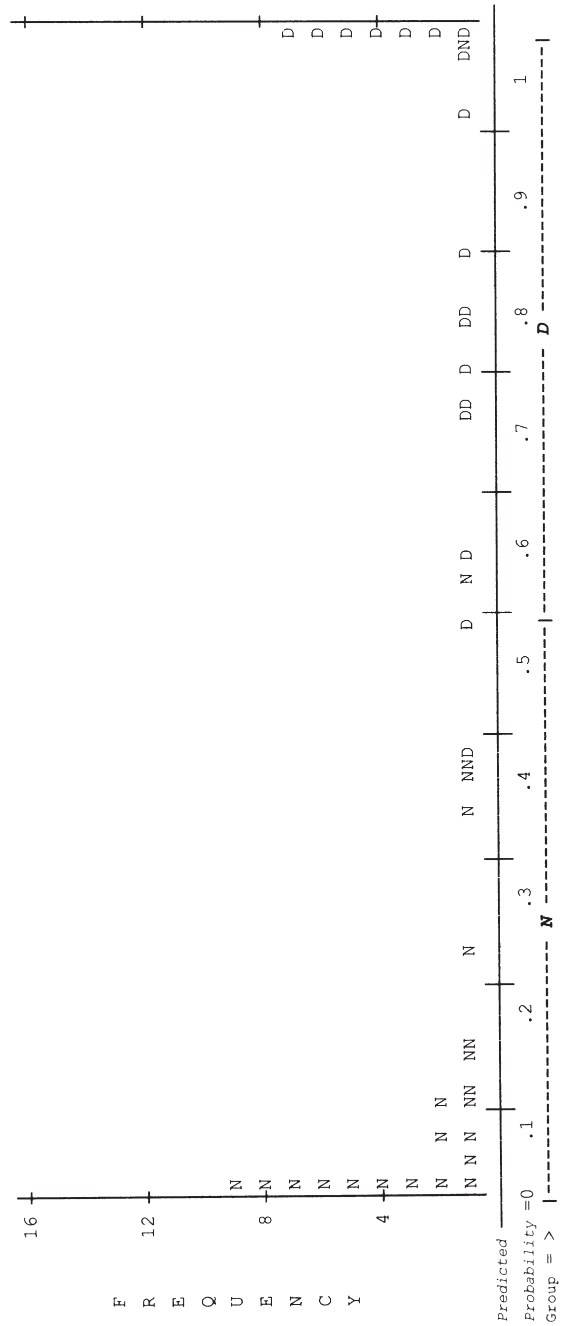
Table 10. Comparison of misclassification rates of several bankruptcy prediction studies

	Beaver (1966)			*Altman (1968)*			*Gritta, et al. (2000)*			*Gudmundsson (1998)*			*Gudmundsson*		
Method	*Univariate*			*MDA*			*NN (U.S. small airlines)*			*LRA (U.S. N.E. airlines)*			*LRA (Int. airlines)*		
Years prior to failure	Overall %	Type I %	Type II %	Overall %	Type I %	Type II %	Overall %	Type I %	Type II %	Overall %	Type I %	Type II %	Overall %	Type I %	Type II %
1	13	17	4	5 (27)	2 (1)	1 (14)	12	3	1	17	3	3	9.8	2	2
2	21	26	6	18	9	2				25	5	4	12	3	2
3	23	28	6	52						28	5	5	26	7	4
4	24	29	2	71											
5	22	23	3	64											

1. Figures in parentheses test against holdout sample. Figures not in parentheses are tested against same sample from which dichotomous classification test was estimated.

2. Type I error is misclassifying a failed firm. Type II error is misclassifying a non-failed firm.

3. Type I and II errors were only presented for the first two years.



Predicted Probability is of Membership for Distress. The Cut Value is 0.50. Each Symbol Represents 1 Case.
Symbols: N - Non-distress
D - Distress

Figure 3. Observed groups and predicted probabilities of distress

conceptual relationship a priori and eliminated unnecessary variables based on correlation analysis. Thus, we believe that our model is conceptually more robust than if a traditional approach was used, that is selecting variables based on prediction ability alone.

The main limitation of this study is that we were unable to test the results on a hold-out sample. However, based on Edmister (1972), we have a reason to believe that our approach of eliminating variables from the initial set based on correlation analysis will reduce the sample specificity of the model.

CONCLUSION

The model demonstrated a fairly high prediction capability of 90.2 percent overall. Compared to other usual benchmark models (see Table 10) such as the Beaver (1966) and Altman (1968) models the performance of the model was superior in first and second years prior and almost matching Beaver's results in the third year prior. For airline models the model had superior performance to Gritta et. al. (2000) Neural Network model in the first year prior. The same applied to the non-financial LRA model specified by Gudmundsson (1998) for U.S. new-entrant airlines, which was outperformed in first and second years prior.

This research has demonstrated that an international distress prediction model seems to be feasible given that political and economic environment variables can be specified and included to capture the impact of important differences between operating environments of international airlines.

Another important new feature of our approach is the inclusion of effective prediction variables pertaining to productivity of the fleet and employees. Previous research, especially Oum and Yu (1998) demonstrated the importance of these measures to distinguish between profitability of the world airlines. But most importantly, this research used a conceptual framework to guide variable selection a priori. This is unusual in failure prediction studies, as most studies allow the selection of variables according to prediction capability only,[11] rather than using a conceptual foundation. Past research on failure prediction models has not improved the understanding of failure processes much, but rather improved the statistical methodology in segregating the two states in the dichotomous variable. It is hoped that this research has demonstrated that conceptual underpinning of a model can lead to as good of results from as those traditional non-conceptual models.

Although this study had a conceptual foundation and good prediction results, only two of the prediction coefficients were significant. This poses problem in interpreting the relationships between variables and distress and non-distress. Yet we can state with confidence that each variable in combination with other variables is effective in distinguishing between distressed and non-distressed airlines. Yet, the two significant variables in the model allow us to state that airlines with relatively high average age of the aircraft fleet and more employees per aircraft are more likely to be in a distressed state. Thus, it is a worthwhile research project to examine the relationship of these two factors on airline performance in detail.

All in all, prediction results for our international prediction model are promising and do lend some confidence to the viability of a multi-country model. It is, however, essential that differences in economic and political environments are captured in such a model as was accomplished in the research presented here.

ENDNOTES

1. The resulting models can be based on financial ratios, non-financial ratios or a mixture of both.

2. The Neural Network approach is the most recent development in this stream of research.

3. See a good discussion on these issues in Tam and Kiang (1992).

4. Most common aircraft brands are Boeing, Airbus, MDC, etc.

5. This assumption is based on the historic fact that governmentally owned airlines are usually bailed out in times of financial crises.

6. The technical insolvency also goes by the name of insolvency on a (cash) flow basis and the insolvency in a bankruptcy sense as an insolvency on a stock basis.

7. These proportions in each group are not representative for the airline industry at large.

8. The approach may have positive impact on the 2 or 3 years prior to testing of the model for the distressed group.

9. No category was, however, empty as a result of the correlation test.

10. Forward or backward elimination is the usual approach in constructing prediction models. However, the approach leads to a model with no conceptual foundation at all.

11. Some studies select ratios according to popularity in other studies, which does not provide any better conceptual foundation for variable selection.

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