



NEW YORK UNIVERSITY
STERN SCHOOL OF BUSINESS
FINANCE DEPARTMENT

Working Paper Series, 1996

Business Failure Classification Models: An International Survey

Altman, Edward I. and Paul Narayanan

FIN-96-5

Business Failure Classification Models: An International Survey

Edward I. Altman and Paul Narayanan

May 1996

Dr. Altman is the Max L. Heine Professor of Finance, Leonard N. Stern School of Business. Mr. Narayanan is an independent financial consultant. Both were co-authors on one of the pioneering works in business failure classification models, the Zeta score model (1977).

Business Failure Classification Models: An International Survey

Edward I. Altman and Paul Narayanan

INTRODUCTION

Business failure identification and early warnings of impending financial crisis are important not only to analysts and practitioners in the United States. Indeed, countries throughout the world, even non-capitalist nations, have been concerned with individual entity performance assessment. Developing countries and smaller economies, as well as the larger industrialized nations of the world, are vitally concerned with avoiding financial crises in the private and public sectors. Some policy makers in smaller nations are particularly concerned with financial panics resulting from failures of individual entities.

From the late 1960s to the present day, numerous studies in the United States were devoted to assessing one's ability to combine publicly available data with statistical classification techniques in order to predict business failure. Studies by Beaver (1967) and Altman (1968) provided the stimulus for numerous other papers. One of the first attempts at modern statistical failure analysis was performed by Tamari (1964). We will not discuss his work here, but we point out its pioneering status. A steady stream of failure prediction papers have appeared in the English literature, and numerous textbooks and monographs include a section or chapter on these models. [For example, see Brigham and Gapenski, 1994, Chapter 23]. What has gone relatively unnoticed is the considerable effort made to replicate and extend these models to environments outside the United States. With the exception of two special issues of the *Journal of Banking and Finance* (1984 and 1988), edited by one of the authors of this article, there is no work with which we are familiar that attempts to survey these studies and to comment on their similarities and differences. The purpose of this paper is to do just that.

We survey the works by academics and practitioners in 21 countries and give references to several other studies. This survey will bring together these myriad studies and highlight study designs, innovations and outcomes that will be of practical value to researchers and practitioners. While the economic forces shaping the outcomes in various countries may diverge, the researchers share a striking similarity in their approach to distress prediction. For example, nearly every study contrasts the profile of failed firms with that of healthier firms to draw conclusions about the coincident factors of failure. Causal studies of failure appear to be comparatively rare.

In several of the countries studied, notably Brazil, France, Canada, Australia, Korea, Mexico and Italy, the authors of this article have participated directly in the construction of a failure classification model. In many cases, we can present an in-depth discussion of the models including individual variable weights. In others, we present the models in more general terms due to the lack of precise documentation in the original article. In general, to make this survey useful to researchers and practitioners alike, we attempt to summarize the contents of the models under the following headings:

1. Modeling techniques used:

While multiple discriminant analysis (MDA) continues to be the most popular technique, researchers have tried other techniques such as multi-nomial logit analysis, probit analysis, recursive partitioning (decision tree analysis), Bayesian discriminant analysis, survival analysis and neural networks. For a variety of reasons, MDA appears to be a *de facto* standard for comparison of distress prediction models. Where the authors have used a technique other than MDA, they usually have compared its results with those from MDA. It is interesting to note that MDA results continue to compare favorably with the other techniques.

2. Data issues:

The size of the sample used and the sources of data are oftentimes critical in assessing the statistical validity of results as well as in the planning of replication or extension type studies. As in many areas of empirical research, the sophistication of the techniques is often not matched by the availability of good data, especially data on failed firms. This problem tends to be more pronounced in the smaller economies of some of the developed countries and in the case of most developing countries. As is common in all empirical research, the randomness and the size of the sample used are mentioned because they are generally indicative of the degree of confidence that may be placed in the conclusions being drawn.

3. Definition of "failure" and "non-failure":

Most models employ a sample of two a priori groups consisting of "failed" and "non-failed" firms. Depending on the inclination of the researcher or on the local conditions, the definition of a failure may vary. Some examples are, bankruptcy filing by a company, bond default, bank loan default, delisting of a company, government intervention via special financing, and liquidation. Closely tied to the failure event is the date of the event. The quality of almost all conclusions drawn about how "early" the distress prediction was depends upon where the analyst placed the date of failure. The healthy firms data is, by definition, "censored" data because all that can be said of the healthy firms

is that they were healthy at the time the sample was taken. It has been found, for example, that some firms that appear to be Type II errors by a model (healthy firms classified as failures) turned out to have failed at a later time.

4. Test results:

It is customary to expect test statistics (such as the t and F statistics) to indicate the statistical significance of the findings. While this is done to establish a baseline for measurement, it is important to note that useful conclusions may be drawn from even small sample studies. In-sample and Out-of-sample or hold-out results, Type I and Type II results, and analyst-modified results are also reported where available.

Developing and Developed Country Models

The failure prediction models reviewed in this chapter may be broadly grouped into two homogeneous categories: developed country models and developing country models. The classification of a country as a "developing" or a "developed" country in this survey is in the context of failure prediction and may deviate somewhat from the traditional grouping of the country.

The main characteristics of developed country models are: 1) failure prediction studies have a long history, 2) corporate financial data are more readily available, 3) failure is easier to identify because of the existence of bankruptcy laws and banking infrastructures 4) government intervention is somewhat less, but not nonexistent and 5) there is a more sophisticated regulation of companies to protect investors. The developing country models are characterized by the relative absence of the above factors. In developing countries, where free market economies have not taken hold, a company's failure is harder to see because of the degree of protection provided by the government. However one may also point to similar practices in developed countries, notably the UK, Germany, Japan, to a lesser extent, and even the U.S on some rare occasions, e.g., Chrysler (1980).

Table 1 summarizes the 39 studies from 21 countries included in this survey.

Table 1
List of International Studies Surveyed

Developed Countries	Japan	Takahashi, Kurokawa & Watase (1979) Ko (1982)
	Germany	Stein (1968) Beermann (1976) Weinrich (1978) Gebhardt (1980) Fischer (1981) von Stein & Ziegler (1984) Baetge, Huss & Niehaus (1988)
	England	Taffler & Tisshaw (1977) Marais (1979) Earl & Marais (1982)
	France	Altman, et al (1973) Mader (1975, 1979, 1981) Collongues (1977) Bontemps (1981)
	Canada	Knight (1979) Altman & Lavallee (1981)
	The Netherlands	Bilderbeek (1977) van Frederiklust (1978) Fire Scoring System (de Breed - 1996)
	Spain	Briones, Marin & Cueto (1988) Fernandez (1988)
	Italy	Cifarelli, Corielli, Foriestieri (1988) Altman, Marco & Varetto (1994)
	Australia	Castagna & Matolcsy (1981) Izan (1984)
	Greece	Gloubos & Grammatikos (1988) Theodossiou & Papoulis (1988)
Developing Countries	Argentina	Swanson & Tybout (1988)
	Brazil	Altman, et al (1979)
	India	Bhatia (1988)
	Ireland	Cahill (1981)
	South Korea	Altman, Kim & Eom (1995)
	Malaysia	Bidin (1988)
	Singapore	Ta and Seah (1988)
	Finland	Suominen (1988)
	Mexico	Altman, Hartzell and Peck (1995)
	Uruguay	Pascale (1988)
	Turkey	Unal (1988)

While we believe this international treatment of failure prediction models is the most comprehensive effort to date, we recognize that some relevant works will possibly be overlooked in this survey and apologize for any omission. Note: The term "author" or "authors" in the succeeding paragraphs pertain to the authors of the respective articles not to the authors of this review.

Emerging Markets Application

One of the models presented in this chapter was developed by Altman, Hartzell and Peck (1995) to rate the credit quality of emerging markets corporate debt. We discuss it below in the context of Mexico -- one of the prime countries whose companies have tapped the international bond markets in recent years. This application has particular relevance since the vast majority of Mexican, Latin American, and emerging market countries' corporate debt in general, is as yet still unrated by the major rating agencies. The model is a variation on the original Z-Score model developed by Altman (1968).

JAPAN

In Japan, bankruptcies are concentrated in the small and medium-size firms, especially those that do not enjoy the protection of an affiliated group of companies. These groups, known as 'Keiretsu', usually involve a lead commercial bank and a number of firms in diverse industries. Still, a number of larger firms listed on the first section of the Tokyo Stock Exchange have succumbed to the negative economic reality of failure. A comparison of the business failures in Japan and the United States may be made based on these statistics appearing in the **Failure Record** published by Dun & Bradstreet and **Tokyo Shoko Koshinso**, among others. There have been a number of studies concentrating on failure prediction in Japan -- most were built prior to 1984. Although we will discuss just two, the reader can find reference and discussion to at least a half dozen more in Altman (1983).

Takahashi, Kurokawa and Watase (1979)

Using multiple discriminant analysis, over 130 measures on individual firms, 36 pairs of failed and non-failed manufacturing firms listed on the Tokyo Stock Exchange in the period 1962-76 and 17 different model types, the authors have constructed a failure prediction model using the following measures:

- Net worth/Fixed assets
- Current liabilities/Assets
- Voluntary reserves plus unappropriated surplus/Total Assets
- Borrowed expenses (interest)/Sales
- Earned surplus

Increase in residual value/Cash sales
 Ordinary profit/Total assets
 Value added (sales - variable costs)

The authors suggest that their model could be more accurate than Altman's (1968) because of (1) its simultaneous consideration of data from one, two and three years prior to failure, (2) its combination of ratios and absolute numbers from financial statements, (3) its utilization of the cash basis of accounting from financial statements as well as the accrual base, and (4) its adjustment of the data when the firm's auditors express an opinion as to the limitations of the reported results (window dressing problem).

It was found that models with several years of data for each firm outperformed a similar model with data from only one year prior to failure. Further, absolute financial statement data contributed to the improved classification accuracy and data from financial reports prepared external to the firm on an accrual basis were more predictive than those prepared from an 'investment effect' or cash basis method. Adjusting the data to account for auditor opinion limitations improved the information content of the reported numbers and ratios. A holdout sample of four failed and 44 non-failed firms was tested with the selected model. The four failed firms went bankrupt in 1977, that is, the year after the last year used in the original model.

One problem with the above model might be the use of several years of data for the same firm in order to construct a model. The authors apparently were aware of this problem but felt it was not serious. While this technique may be superior to the sometimes-advocated technique of utilizing several models, each based on a different year's data [e.g. Deakin (1972)], it still remains that the observations are not independent from each other. That is, while the 36 firms are independently drawn observations, the three years of data for each firm are not.

The accuracy of this model on the original and holdout samples was simulated based on various cutoff score criteria. The Type I error was found to be quite low for the original sample (range of 0.0% to 16.7% error rates) and virtually nil on the very small four-firm holdout failed firm sample. The Type II error rates ranged greatly, from 0.0% to 52.8%, indicating the tradeoff between Type I and Type II errors as one varies the cutoff score.

The authors spend considerable effort to discuss the derivation of cutoff scores based on various assumptions of prior probabilities and cost of errors. In essence, Takahashi et al. simulate various assumptions and leave the choice of a cutoff score up to the individual user.

Ko (1982)

Ko's sample included 41 pairs of bankrupt and non-bankrupt entities from 1960 through 1980. Several accounting corrections, adjustments, and transformations, in addition to variable trends, were applied to the data set in order to reduce the biases held to be inherent in conventional Japanese reporting practices. He compared the standard linear model design against a model with first order interactions and, also a quadratic model. He also examined a discriminant model using factor analysis for orthogonal variable transformation. On the basis of classification results, a five-variable linear independent model, without the orthogonal transformations, was selected as the best model; it yielded a 82.9% correct classification rate by Lachenbruch (1967) tests versus a 90.8% for the original sample set. It is interesting to note that the linear interaction design appeared best on the basis of group separations potential, but not for classification accuracy.

Ko found, with respect to the variables of the model, that each sign was in agreement with each variable's economic meaning and that three of the variables are similar to those in Altman's 1968 model. They are: EBIT/sales, working capital/total debts, and market equity/total debts. A fourth variable in this model is an inventory turnover change ratio. His last ratio was the standard deviation of net income over four periods. The final standardized coefficient model is of the form

$$Z_j = 0.868X_1 + 0.198X_2 - .048X_3 + 0.436X_4 + 0.115X_5,$$

where

X_1 = EBIT/sales,

X_2 = inventory turnover two years prior/inventory turnover three years prior,

X_3 = standard error of net income (four years)

X_4 = working capital/total debt,

X_5 = market value equity/total debt,

Z_j = Z-score (Japanese model),

The standardized form results in a zero cutoff score; that is, any score greater than zero indicates a healthy situation, with probability of classification of bankruptcy less than 0.5, and probabilities greater than 0.5 for negative scores.

SWITZERLAND
Weibel (1973)

While bankruptcy classification and its many implications have interested researchers in Germany for many years, the earliest major work published in German was performed in Switzerland by Weibel (1973). He constructed a sample of 36 failed Swiss firms from 1960 to 1971 and matched them to a like number of non-failed firms in terms of age, size, and line of business. Using univariate statistical parametric and non-parametric tests, Weibel analyzed ratios of these two groups in much the same way that Beaver (1967) did. He found that many of the individual ratios were non-normal and so he abandoned multivariate tests, [We have often referred (Altman et al., 1977) to the non-normality problem which exists in many economic and financial data sets but we prefer to test the robustness of models using such data rather than abandoning the tests. We do observe that some European researchers have found multivariate studies suspect due to the non-normality properties of financial measures].

Out of 41 original ratios, Weibel selected 20 for dichotomous comparisons. He utilized cluster analysis to reduce collinearity and arrived at the conclusion that six ratios were especially effective in discriminating among the paired groups. Three ratios were types of liquidity measures with one (near monetary resource assets-current liabilities/operating expenditures prior to depreciation) performing best. He also found that inventory turnover and debt/asset ratios were good individual predictors. He examined the overlapping range of individual ratios for the two groups and presented some *ad hoc* rules for identifying failures. He then divided the observations into three risk groups. The low-risk group had all six ratios in the interdecile range of good firms; high-risk firms had at least three ratios in the interdecile range of failed companies; and a final category was identified where the firm does not fall into either of the other two groupings. Weibel's results were quite accurate in the classification stage; we have no documentation on how his "model" performed on hold-out tests and what has been the evolution of models in Switzerland since his original work.

GERMANY
Beerman (1976)

Many studies in Germany have investigated the causes and problems of insolvencies, especially for financial organizations, e.g., von Stein (1968). Beermann (1976) published one of the first German statistical classification models for insolvency analysis. He examined matched groups of 21 firms which operated or failed in 1966 through 1971. Applying dichotomous and linear discriminant tests, he analyzed 10 ratios encompassing profitability, cash flow, fixed asset growth, leverage, and turnover. His results, using the difference in means dichotomous

test, were mixed, with one ratio type (profitability) yielding quite respectable results. The other ratios were far less impressive on a univariate basis.

Beermann advocates using discriminant analysis, and his 10-ratio model yielded classification error rates of 9.5%, 19.0%, 28.6%, and 38.1% for the four years prior to failure. He does not indicate which model to use, and the coefficients of each measure were quite unstable in the four different year models. Also, we are given no indication of holdout test results or predictive accuracy and, due to the small sample, we do not have confirming evidence of the model(s) reliability.

Weinrich (1978)

Weinrich's (1978) book, from his dissertation, attempted to construct risk classes in order to predict insolvency. His sample of failed firms was considerably larger (44) than Beermann's, concentrating on small and intermediate-size firms, with average sales of DM 4 million (less than \$2 million), that failed from 1969 through 1975. Weinrich considered three consecutive annual financial statements (Years 2 through 4 prior to failure) but did not utilize the one statement closest to insolvency. This is a marked difference from most of the other models we have studied.

Weinrich abandoned the use of parametric classification techniques because of his feeling that many assumptions were violated (normality, variance homogeneity of groups, and high correlation amongst the variables). His linear discriminant models were quite good in terms of classification accuracy (11% error for Year 2, 15.7% and 21.9% for Years 3 and 4, respectively).

Weinrich did use factor analysis and found the technique useful, indicating at least six different factors that explained 80% of the variance of the ratios. He then devised a model of credit-worthiness that contained eight relatively independent ratios and utilized both univariate and multivariate methods. A point evaluation system was devised based on quartile values of good and bad firms. For example, a net worth/debt ratio over 43.3% receives the best (lowest) point value. A firm with significant insolvency potential is one with 24 points or more (an average of three for each of the eight ratios). This arbitrary point system correctly classified over 90% of the failed firms two years prior to failure, but was only 60% accurate three years prior. The Type II error rate was quite high, averaging well over 20% in each year. Weinrich advocated the use of trend analysis of the point system as well as the point estimate.

Gebhardt (1980)

Gebhardt (1980) compared dichotomous and multivariate

classification tests of samples of failed and non-failed firms based on models constructed before and after the 1965 Financial Statement Reform Law. The earlier model contained 13 matched pairs of industrial firms and the post-1965 model contained 28 pairs. He utilized a very large number of possible financial indicators which were reduced to 41 ratios for the dichotomous tests. He also incorporated crude measures of misclassification costs and tested his results with the Lachenbruch (1967) holdout test procedure. Gebhardt, like others, felt that the non-normality of some ratios implied the use of non-parametric procedures but found those results unsatisfactory. The multivariate results were far superior. Gebhardt concluded that the pre-1965 models' results were actually better than the ones following the reform law.

Fischer (1981)

Fischer's work concentrates on non-numerical data for forecasting failure. He is particularly interested in methods of credit evaluation for suppliers who do not have the ability or the data to perform comprehensive conventional analysis on their existing and potential customers. He advocates an electronic data processing system which can retrieve and analyze such non-numerical information as reports from newspapers, magazines, inquiry agencies, and credit information from other sellers. Unfortunately, according to Fischer, commercial rating agencies and banks are constrained as to how honest and revealing they choose to be with regard to their reports. In addition, the information provided may be outdated and certainly contains subjective elements. More than one source of credit information is therefore desirable.

Fischer advocates combining the permanent and transitory information on enterprises with microeconomic and sociopolitical data. Five arbitrary rating categories are devised based on non-numerical data and the delphi technique (numerous experts in various areas) is also recommended. Each characteristic is rated over time into the five categories. The sum of development patterns from varying sources of information builds the basis for a final classification. Clustering techniques are also used by Fischer to clarify information types.

von Stein and Ziegler (1984)

This is an ambitious attempt to identify bankruptcy risk from three separate, yet inter-related perspectives. They are: 1) balance sheet analysis using financial ratios; 2) analysis of the bank accounts of firms and 3) analysis of the behavioral characteristics of company management. The study thus addresses criticism leveled at relying exclusively on one of the three approaches in assessing failure risk.

The balance sheet analysis considers medium sized firms in Germany. The failure dates for the "bads" covered the years from 1971 to 1978. The date for the all the "goods" was fixed (1977). There were 119 failed companies; the failure date was defined as the date of the first value adjustment or write-off, or only in a few cases, the date of the bankruptcy or composition petition. The "goods" consisted of 327 companies. The companies in the "bad" sample were from the following industries: manufacturing and processing (54.5 %), building (17.7%), trade (22.7%), others (5.1). The companies in the "goods" sample were comparably distributed across industries.

Thirteen financial ratios were identified to as the most discriminating of the 140 ratios initially considered. These ratios are:

1. capital borrowed/total capital,
2. (short-term borrowed capital x 360)/total output),
3. (accounts payable for purchases and deliveries x 360)/material costs,
4. (bill of exchange liabilities + accounts payable for purchases and deliveries x 360)/total output,
5. (current assets - short-term borrowed capital)/total output,
6. equity/(total assets - liquid assets - real estates and buildings),
7. equity/(tangible property - real estates and buildings),
8. short-term borrowed capital/current assets,
9. (working expenditure - depreciation on tangible property)/(liquid assets + accounts receivable for sales and services - short-term borrowed capital),
10. operational result/total capital,
11. (operational result + depreciation on tangible property)/net turnover,
12. (operational result+depreciation on tangible property)/short.term borrowed capital,
13. (operational result+depreciation on tangible property)/capital borrowed.

Three non-parametric methods (Nearest-Neighbor Classifications: Fix/Hodges, Loftsgaarden/Quiesenberry and Parzen) and 2 parametric methods (linear and quadratic multiple discriminant analysis) were tested. The method of Fix and Hodges was found to be the most discriminating. The results of the tests on the development sample are given in Table 2.

Table 2
Classification Results - Fix/Hodges Non-parametric Model

Group	Year Before Fixed Date	Correct Classification
	5	71.4%
	4	78.2
Bad cases	3	86.6
	2	89.9
	1	95.0
Good cases	1977	83.7

In the second phase of the analysis, 45 bad and 37 good cases were examined using the following account characteristic variables:

1. Average balance with regard to value dates
2. Most favorable balance for the borrower
3. Most unfavorable balance for the borrower
4. Credit turnover
5. Debit turnover
6. Bill of exchange credits
7. Cheque credits
8. Transfer credits
9. Cash deposits
10. Bill of exchange debits
11. Cheque debits
12. Transfer debits
13. Cash payouts
14. Limit

Profile analysis, dichotomous classification and linear discriminant analysis were the three techniques applied on the data. All three methods revealed important differences between the bad and the good companies. Linear discriminant analysis provided the best results. The function contained the following variables:

1. (Most favorable balance for the borrower)/Limit
2. (Most favorable balance for the borrower)/Debit turnover
3. Cheque debits/Debit turnover
4. Debit turnover/Limit
5. Bill of exchange debits/Debit turnover
6. Transfer credits/Credit turnover

The classification results on the development sample are shown in Table 3.

Table 3

Semi-annual period before fixed date	Correct Classification	Correct Classification of Good cases
8	73.3%	89.2%
7	66.7	83.8
6	75.6	81.1
5	80.0	89.2
4	82.2	78.4
3	91.1	78.4
2	88.9	83.8
1	88.9	83.8

The third phase of the study attempted to identify the characteristics and concrete behavioral indications that distinguish the failed firms from the solvent ones. The authors used a psychological technique named "nomethetical assessment" and the "principle of simultaneous vision". The later term is taken to mean that the authors looked for factors consistently found in the failed group that are consistently absent in the non-failed groups. The investigation was based on 135 bad companies and 25 good companies and consisted of a) an examination of the functional areas of the companies leading to their weak points and b) partly standardized interviews of bank lending personnel most familiar with the history and behavioral characteristics of the owner/managers.

The qualities found to set the failed company management apart were the following:

1. Being out of touch with reality
2. Large technical knowledge but poor commercial control
3. Great talents in salesmanship
4. Strong-willed
5. Sumptuous living and unreasonable withdrawals
6. Excessive risk-taking

The management of the solvent companies were found to be more homogeneous than the failed companies and seldom showed a lack of consciousness of reality. The authors recommend all three components of analysis (balance sheet, account behavior and management) be pursued to assess a company.

Baetge, Huss & Niehaus (1988)

This study reports the results of a multiple discriminant

analysis model whose aim is to identify at least 80 percent of the endangered corporate borrowers three years before they become distressed.

The bad borrowers were defined as those that resulted in a final credit loss to the bank or wherever a temporal delay occurred or was feared in the payment of the obligations of the borrower as stipulated by contract. Good borrowers were those that did not possess the above characteristics. Samples were drawn from both bad and good enterprises representative of the line of business, legal form and size. Principal component analysis was used to reduce the initial universe of 42 financial ratios to seven factors. These factors in turn led to a three variable MDA model consisting of the following ratios:

Capital structure: $\text{Net worth} / (\text{Total assets} - \text{quick assets} - \text{property and plant [without equipment]})$

Profitability: $(\text{operating income} + \text{ordinary depreciation} + \text{addition to pension reserves}) / \text{total assets}$

Financial Strength: $(\text{cash income including extraordinary income} - \text{cash expense including extraordinary expense}) / \text{short term liabilities.}$

Rather than using the cutoff point as the basis for separating the firms into good and bad groups, the authors created a gray area around the cutoff point where the probability of assigning to either group was low. By doing so they were able to put the predictive accuracy of the model in a clearer perspective. The discriminant function was subsequently tested with about 40,000 financial statements of all corporate customers of the bank. The results of the tests were quite similar to that found on the analysis sample. The model proved very stable when tested using a simulation model developed at Gottingen University.

ENGLAND

Taffler and Tisshaw (1977)

Taffler and Tisshaw (1977) have approached the corporate distress problem primarily from the viewpoint of security analysis and adaptations of their work, and that of Taffler and Houston (1980) and Taffler (1976). They indicate that their model is also relevant for accounting firms to assess the going concern capability of clients and in their work as receivers and liquidators of firms that have already failed,

Research Design

To construct their solvency model, Taffler and Tisshaw (T&T) utilized linear discriminant analysis on a sample of 46 failed firms and 46 financially sound manufacturing companies. The latter sample was matched to the failed sample by size and

industry (no information on these characteristics available), from period 1969 through 1975. Failed firms were those entering into receivership, creditors' voluntary liquidation, compulsory winding up by order of the court, or government action (bailouts) undertaken as an alternative to the other unfortunate fates. Eighty different ratios were examined for the two samples with a resulting model utilizing only four measures. These four were:

X_1 = profit before tax/current liabilities,
 X_2 = current assets/total liabilities,
 X_3 = current liabilities/total assets, and
 X_4 = no-credit interval.

The first three ratios are taken from the balance sheet and measure profitability, liquidity, and a type of leverage, respectively. The no-credit interval is the time for which the company can finance its continuing operations from its immediate assets if all other sources of short term finance are cut-off. More directly it is defined as immediate assets-current liabilities/operating costs excluding depreciation. T&T state that the no-credit interval is "something akin to the acid-test ratio" (p.52).

Empirical Results

Both the model described above and an "unquoted model" (for non-listed companies) appeared to be quite accurate in classifying correctly over 97% of all observations. Another model by Taffler (1976), supposedly the one being used by practitioners in the U.K. investment community, had accuracies of 96%, 70%, 61%, and 35% for the four years prior to failure.

The nearly perfect one-year-prior accuracy that T&T observe utilizing their model contrasts sharply with the relatively small percentage of quoted and unquoted firms that were assessed to have a going concern problem by their auditors. In fact, T&T report that just 22% of the 46 quoted firms (and none of the 31 unquoted manufacturing bankrupt firms) had been qualified on going concern grounds prior to failure.

Implications

The drop-off in accuracy is quite noticeable as earlier year data are applied, although, for investment purposes, one needs less of a lead time before failure in order to disinvest without losing a major amount of his investment. It is fair to say, however, that as failure approaches. Stock prices tend to move downward in a rather continuous manner, Taffler and Houston (1980) indicated that 12% of large quoted industrial firms had Z scores indicating high failure risk. This is a comparable figure to results we observed utilizing our own ZETA model (Altman, Haldeman, and

Narayanan, 1977) in the United States.

The authors also point out that about 15 to 20% of those firms which display a profile similar to failed companies will actually fail. In addition, the British government appeared to them to be keeping many ailing firms alive. Although this type of paternalism is less common in the United States, examples like Lockheed and Chrysler Corp. periodically crop up. Finally, T&T conclude that accountants are too defensive when it comes to considering the value of conventional published historic statements. When several measures of a firm, described from a set of accounts, are considered together the value of the information derived is enhanced dramatically. Essentially, T&T advocate a multivariate approach to financial analysis, and I certainly agree. It is unfortunate that they did not share with readers a more complete description of their findings and the data used in their analysis. Their results are certainly provocative and appear to be of some practical use in England.

In his latest attempt to revise the company failure discriminant model (Taffler, 1981), a smaller sample of 23 failed companies (1968-73) and 45 non-failed entities displaying financially healthy profiles were examined first within a principal component analysis framework. A large list of almost 150 potential variables was reduced to just five. These five are:

earnings before interest and taxes/total assets,
total liabilities/net capital employed,
quick assets/total assets,
working capital/net worth, and
stock inventory turnover.

The variables were discussed in terms of their discriminant standardized coefficients and other relative measures of contribution, but no function weights were provided. Taffler did utilize prior probability and cost-of-error estimates in his classification procedures. He concludes that such an approach is best used in an operational context as a means of identifying a short list of firms which might experience financial distress (p. 15). Another conclusion is that the actual bankruptcy event is essentially determined by the actions of the financial institutions and other creditors and cannot strictly be predicted by using a model approach.

Other U.K. Studies

Marais (1979), while on a short-term assignment for the Industrial Finance Unit of the Bank of England, also utilized discriminant analysis to quantify relative firm performance. He too concentrated on U.K. industrials and incorporated flow of funds variables with conventional balance sheet and income statement measures. Using a sample of 38 failed and 53 non-failed

companies (1974-I 977), he tested several previously published models from the United States and the United Kingdom using both univariate and multivariate techniques.

He then went on to develop his own model, of which space does not permit a full discussion. His model included the following variables:

X_1 = current assets/gross total assets,

X_2 = 1/gross total assets,

X_3 = cash flow/current liabilities, and

X_4 = funds generated from operations minus net change in working capital to total debt,

His results were considered "satisfactory" and his conclusions modest. He mainly advocated that firms whose scores fell below a certain cutoff point should be regarded as possible future problems; "that all Z scores can hope to do is act as a sophisticated screening device to those firms most urgently in need of analysis" (p. 29).

A later work, by Earl and Marais (1982), expanded upon this work with more enthusiastically reported results and implications. Classification results of 93%, 87%, and 84% respectively for the three years prior to failure are reported. The authors felt that funds flow data improved their classification accuracy. The single ratio of cash flow/current liabilities was a successful discriminator. Subsequent tests on failures and non-failures in 1978 revealed a very low Type I error but an unacceptably high Type II error assessment.

CANADA

Canada, like Australia, is a relatively small country in terms of business population, yet it too is concerned with the performance assessment of individual entities. The economy is very much tied to the fortunes of the United States and its financial reporting standards are often derived from the same accounting principles. Like many other environments, the key constraint in Canada is the availability of a large and reliable data base of failed companies. This requires both a sufficient number of failures and publicly available data on those firms. Both attributes do exist in Canada, but just barely.

Knight (1979)

Knight (1979) analyzed the records of a large number of small business failures as well as conducting interviews with the key

persons involved. The author contends that his study supplies information "to answer the question, why do small businesses fail in Canada and also generates certain guidelines as to how the failure rate in Canada may be decreased from its recent increasing level." Not surprisingly, Knight finds that a firm usually fails early in its life (50% of all failed firms do so within four years and 70% within six) and that some type of managerial incompetence accounts for almost all failures.

Knight also attempted to classify failure using a discriminant analysis model. He amassed a fairly large sample of 72 failed small firms with average sales and assets of about \$100,000. A five-variable discriminant function realized disappointing results, however. Only 64% of the original sample of 36 failed and 36 non-failed firms and 54% of the test sample of a like number of firms were correctly classified. He concluded that the discriminant analysis procedure was not successful. Knight did combine firms in many different industries, including manufacturing, service, retail, and construction and this will contribute to estimation problems, especially if the data are not adjusted to take into consideration industry differences and/or accounting differences, for instance, lease capitalization. We discuss this industry effect at length in the Australian situation.

Altman and Lavallee (1981)

The results of Altman and Lavallee (1981) were more accurate when manufacturing and retailing firms are combined but they do not advocate a single model for both sectors. Indeed, the holdout tests of this study indicate that non-manufacturers cannot be confidently measured when the model contains variables which are industry sensitive.

The Altman and Lavallee (A&L) study was based on a sample of 54 publicly traded firms, half failed and half continuing entities. The failures took place during the ten years 1970-1979 and the average tangible asset size of these 27 failures was \$12.6 million at one statement date prior to failure (average lag was 16 months). Manufacturers and retailer-wholesalers were combined although the data did not enable them to adjust assets and liabilities for lease capitalization. The continuing firms were stratified by industry, size, and data period and had average assets of \$15.6 million. One can observe, therefore, that the Canadian model for the 1970s decade consisted of firms with asset sizes similar to those of the previously reported U.S. models (e.g. Altman, 1968) constructed from the 1950s and 1960s data period.

A&L examined just 11 ratios, and their resulting model contained five based on a forward stepwise selection procedure. The model

for Canada (Z_c) is

$$Z_c = - 1.626 + 0.234(X_1) - 0.531(X_2) + 1.002(X_3) + 0.972(X_4) + 0.612(X_5)$$

where

- Z_c = Canadian Z-score,
- X_1 = sales/total assets,
- X_2 = total debt/total assets,
- X_3 = current assets/current liabilities,
- X_4 = net profits after tax/total debt. and
- X_5 = rate of growth of equity - rate of asset growth.

Classification Results

The overall classification accuracy of the Z model on the original 54-firm sample was 83.3%, which is quite high, although not as impressive as that reported in some of the other economic environments. Practically speaking, classification criteria are based on a zero cutoff score with positive scores indicating a non-failed classification and negative scores a failed assignment. Reliability, or holdout tests, included Lachenbruch (1967) test replications, the original sample broken into randomly chosen classification and test samples, and testing the model on prior years data, for example Years 2 through 4 before failure. The Lachenbruch and replication holdout results showed accuracies very similar to those of the original sample results and the prior year accuracies were 73% (Year 2), 53% (Year 3), and only 30% (Year 4). Therefore, the model appears reasonably accurate for up to two statements prior to failure but not accurate for earlier periods. These findings are quite similar to those of Altman's (1968) model and we can suggest that the similarities in accuracies are partially related to the similarities of the data quality and the somewhat diverse industries represented in the sample.

A&L also simulated their results for various assumptions of prior probabilities of group membership and costs of error. Their findings were that Type I errors could be reduced, even eliminated, but that the resulting Type II error was unacceptably high and vice versa for eliminating the Type II error. The Z model's results were also compared to a naive classification strategy of assigning all observations to the non-bankrupt category or assuming that the resulting errors would be realized in proportion to the actual experience of bankrupts and non-bankrupts [proportional chance model; see Joy and Tollefson (1975)]. They concluded that, in every case, the Canadian Z, model was more efficient; that is, it had a lower expected cost than a naive model.

Finally, A&L observe that the industry affiliations of the misclassified firms were predominantly retailers amongst the failed group and manufacturers among the non-failed. It appeared that one of the variables, sales/ assets (X_1), was particularly sensitive to industry effects, with the misclassified failed retailers all having high asset turnovers and the misclassified manufacturers all with low turnovers.

Implications

A&L attempted to re-estimate the model without the sales/assets variable, but the results actually were worse. One can conclude that the Canadian investigations are at an early stage and follow-up work is needed in subdividing a larger sample into manufacturers and retailers-wholesalers and/or improving the information on critical industry differences, such as lease usage and capitalization. Only additional time will permit analysts to construct models with sufficiently large samples or to witness an improvement in the quality of reported data. We are aware of a move with the Canadian government to set up an early warning system to identify potential large publicly traded firm crisis situations, for instance, Massey-Ferguson. Authorities are currently considering available models such as Altman (1968) and A&L (1980) as alternatives to building their own model.

THE NETHERLANDS

Bilderbeek

Bilderbeek (1977) analyzed a sample of 38 firms which went bankrupt from 1950 through 1974 and 59 ongoing companies. They found that 85 firms had sufficient data for analysis. Bilderbeek analyzed 20 ratios within a stepwise discriminant framework and arrived at a five-variable model of the form:

$$Z = 0.45 - 5.03X_1 - 1.57X_2 + 4.55X_3 + 0.17X_4 + 0.15X_5$$

where,

Z = Z-score (Netherlands, Bilderbeek)

X_1 = retained earnings/total assets

X_2 = added value/total assets

X_3 = accounts payable/sales,

X_4 = sales/total assets

X_5 = net profit/equity.

Two of the five signs (coefficients), X_4 and X_5 , are positive and contrary to expectations since, for this model, negative scores indicate a healthy situation and positive scores indicate a failure classification. His model was based on observations over five reporting periods prior to failure and is not based on one-year intervals. His results were only mildly impressive, with accuracies ranging from 70 to 80% for one year prior and remaining surprisingly stable over a five-year period prior to failure. He explains in his book (1979) that the stability is due to the facts that there are no liquidity variables and the stable role of the value added measure. Subsequent tests of Bilderbeek's model have been quite accurate (80% over five years). Apparently, several institutions are now using his model for practical purposes.

Van Frederikslust

Van Frederikslust's (1978) model included tests on a sample of 20 failed and a matched non-failed sample of observations for 1954 through 1974. All firms were quoted on the Netherlands Stock Exchange. In addition to the now traditional research structure, that is, linear discriminant, single year ratio, equal a priori probability of group membership assumptions, the author performed several other tests. Those included (1) looking at the development of ratios over time (temporal model) as well as analyzing ratio levels, (2) varying the a priori assumption of group membership likelihood to conform with a specific user of the model (e.g., lending officer), and (3) varying the expected costs of the models, taking into consideration the specific user's utility for losses.

Van Frederikslust attempts to provide a theoretical discussion for his choice of variables. He concludes that traditional measures of firm performance, that is, liquidity, profitability, solvency, and variability of several of these categories, are the correct indicators. Industry affiliation and general economic variables are also thought to be important but are not included in his model. In fact, the primary model only contained two variables representing liquidity and profitability.

Van Frederikslust's primary model analyzed the level of ratios.

His definition of failure included many different types but essentially involved the failure to pay fixed obligations. His sample included textile, metal processing, machinery, construction, retailing, and miscellaneous firms. The non-failed group (20) were randomly selected from the same industries, size categories (assets), and time periods as was the failed group. His first model was:

$$Z_{NF} = 0.5293 + 0.4488X_1 + 0.2863X_2$$

where

- Z_{NF} = Z-score (Netherlands, Frederikslust),
 X_1 = liquidity ratio (external coverage), and
 X_2 = profitability ratio (rate of return on equity).

The author distinguishes between the *internal coverage ratio* (cash balance + resources earned in the period/short-term debt) and the *external coverage ratio* [short-term debt in period t plus available short-term debt ($t-1$)]. The external coverage measures what can be expected from the renewal of debt and additional debt. "Failure at moment (t) is completely determined by the values of internal and external coverage at that moment" (p. 35). Van Frederikslust uses only the external coverage measure in his "simple" model.

Separate models are developed for each year, as Deakin did (1972). The arguments for this are that a separate model is necessary to assess failure probabilities for different time periods and that the distributions of ratios vary over time. While we do not necessarily agree that separate models are desirable--indeed, they could be confusing--the discussion on timing of failure prediction is a useful one. The classification program utilized was actually a 0.1 multiple regression structure and not the discriminant analysis model used in most other studies. Fisher (1936) has shown that the coefficients of these structures are proportional when dealing with a two-group model.

The results for the one-period model indicate that the estimated chances of misclassification into the two groups are 5% for the failed group and 10% for the non-failed group. The expected accuracy falls as time prior to failure increases. For example, the error rates are 15% and 20% respectively for two years prior.

A revised model, analyzing the development of ratios over time, yielded an equation which utilized the liquidity ratio in the

latest year before failure, the profitability ratio two years prior, the coefficient of variation of the liquidity ratio over a seven-year period, and the prediction error of the profitability ratio in the latest year before failure. Again, separate models were developed for each year prior to failure. Using Lachenbruch's procedure for estimating error rates, the results were quite similar to those of the first set of equations based on the two variable, "levels" ratios. Accuracies for earlier years did show slight improvements.

The Fire Scoring System - de Breed and Partners (1996)

A small consulting firm in the Netherlands recently developed specialized credit scoring models for specific industries in Holland. Utilizing discriminant analysis techniques, like many of the other studies discussed earlier, the unique aspect of these models is their specific industry orientation and the very large data bases of failed and un-failed companies maintained and updated. In 1996, the firm published a type of "Micheline Guide" for rating the health of Dutch companies, using a zero to four star system. Since the models are proprietary, we cannot comment further.

FRANCE

Altman, Margaine, Schlosser & Vernimmen (1973)

Mader (1975, 1979, 1981)

Collongues (1977)

Bontemps (1981)

In France, the business failure rate increased dramatically in 1981 to 20,895 firms, a jump of 20% over 1980. Altman et al. (1973) first attempted to apply credit scoring techniques to problem firms, many of which filed for bankruptcy (*faillite*). Working with a sample of textile firms and data provided by Banque de France, this study applied principal component analysis to a large number of financial indicators and proceeded to utilize the most important ones in a linear discriminant model. Their results were at best mediocre on test samples and, while the model did provide insights into that troublesome sector, it was not implemented on a practical basis.

A more recent study by Bontemps (1981), using a large sample of industrial companies and data from the Centrale de bilans of Credit National (supplier of long-term debt capital to French

firms), achieved high accuracy on original and holdout tests. His results are quite interesting in that as little as three variables were found to be useful indicators. Bontemps combined both the univariate technique developed by Beaver (1967) with arbitrary, qualitative weightings of the three most effective measures to classify correctly as much as 87% of his holdout sample of 34 failed and 34 non-failed firms. The original function was built based on a matched (by industry, size, and year) sample of 50 failed and non-failed entities from 1974 through 1979.

Collongues (1977), Mader (1975, 1979, and 1981) also have attempted to combine financial ratios with data from failed and non-failed French firms. Mader's studies were descriptive of firms in difficulty and the utility of ratios as risk measures. These have led to several multivariate studies performed by the Banque de France in their centrale de bilans group. Collongues did utilize discriminant analysis in his analysis of small and medium-size firms with some success.

The application of statistical credit scoring techniques in the French environment appears to be problematic, but the potential remains. One problem usually is the quality of data and the representativeness of them. But this is a problem in all countries and is not unique to France. The government has gone on record on several occasions as intending not to keep hopelessly insolvent firms alive artificially but to try to assist those ailing firms prior to total collapse. An accurate performance predictor model could very well help in this endeavor.

SPAIN

Fernández (1988)

This study describes an empirical model to objectively evaluate and screen credit applicants. The work consists of the determination of the model with two objectives: (1) to check the validity of financial ratios as prediction tools, and (2) to predict a firm's collapse.

The research sample consisted of 25 failed and 25 non-failed firms, with an additional 10 each being set aside for validation testing. Data pertaining to 2 years preceding the failure was collected. Only data pertaining to 1978-82 was permitted in order to eliminate the possible distortion caused by the natural

changes in ratios caused by the business cycle. The ratios were examined using three techniques:

1. Univariate analysis
2. Factor analysis by principal components
3. Discriminant analysis

The author concludes that univariate analysis is not practical given the volume of the ratios to be considered and the possible interactions among the ratios. In addition, the univariate ratio analysis has to be performed in the context of the market in which the firm operates, thus the ratios show only relative position of the company. Lastly, multivariate ratios can improve analyst productivity and free him/her to concentrate on other equally important matters such as the credit terms, maturity, guarantees etc.

When there are a large number of variables to be considered, principal component analysis is a way to eliminate the variables that carry the same information and reduce the observation to a handful factors or "principal components". Each principal component is a linear combination of one or more of the underlying variables. The coefficient of the underlying variable in the factor equation is called the "factor loading". In this study the author conducted factor analysis in two ways: (1) without rotation of the factors and (2) using varimax rotation to ensure the independence of the resulting factors.

The second way is believed to produce more desirable (i.e., stabler) results when used as independent variables in regression or discriminant analysis.

The author found that 8 factors existed that account for 79.3 percent of the information contained in the initial set of ratios. Just two factors provide for 42.1 percent of the information. The eight factors are:

Capacity to repay the debts

Liquidity

Fixed assets financing

Efficiency of the firm
 Rotation of fixed assets
 Profitability of permanent funds
 Structure of working capital
 Structure of short-term debt

Fourteen ratios with a higher loading from the principal components were selected as input for the discriminant analysis procedure. A six variable discriminant function emerged as the best, with an overall classification accuracy of 84 percent in the original sample. The discriminant function is as follows:

$$Z1 = - 0.26830V3 + 0.54666*V4 + 0.55483*V6 + 0.62925*V9 \\ - 0.514119*V12 + 0.43665*V17,$$

where

V3 = (Permanent funds/Net fixed assets) / Industry value,

V4 = Quick ratio/Industry value,

V6 = Cash-flow/Current liabilities,

V9 = Return on investment,

V12= Earnings before taxes/sales,

V17= Cash-flow/sales.

The results of the model on the development sample and the hold out sample are given in Table 4. As expected, there is a slight drop in performance of the model in the hold out sample. Of greater concern is where the drop in performance is: normally the Type I accuracy will be maintained and the Type II accuracy will be lower. In this case, the Type I accuracy has a dropped from 84 percent to 70 percent. Some follow up analysis of the Type I and Type II errors by individual case may have been useful. The author compared the discriminant model using the underlying ratios (described in the foregoing) with a discriminant model using the factor scores and found that the percentage accuracy of classification was the same in both cases. This is an interesting result for future researchers.

Table 4
Classification results

Actual Group	No of Cases	Predicted Group Membership	
		1	2
Group 1	25	21	4
		84.0 %	16.0%
Group 2	25	4	21
		16.0%	84.0%

Overall classification accuracy: 84.0 %

Briones, Marín, Cueto (1988)

This study presents the results of empirical research undertaken to build a multivariate model to forecast the possible failure of financial institutions in Spain and their takeover by the monetary authorities or regulatory agencies.

During the period 1978-83, Spain underwent a serious crisis in its financial institutions. Roughly 47 percent of all Spanish banks failed during this period; 21.4 percent of the equity and 18.7 percent of the deposits were affected by the problem banks. Banco de Espana (the Spanish equivalent of the Federal Reserve) working through Fondo de Garantía de Depósitos (the Spanish equivalent of the Federal Deposit Insurance Corporation) carried out the resolution of the banks through "administrative solutions". Legal solutions such as bankruptcy procedures were not used for fear of causing a panic. A bank may thus be technically insolvent when it has a liquidity crisis or it may be definitively insolvent when there is negative net worth. Since a "failed" institution can operate indefinitely with assistance from the regulators, the authors have defined a bank to have failed if there an intervention by Fondo de Garantia Depósitos.

The sample consisted of 25 failed banks and equal number of non-failed banks paired up based on the 5 year average size of deposits during the period prior to intervention. The data sources were Anuario Estadístico la Banca Privada published by the Consejo Superior Bancario and the memorandum of the Fondo de Garantía de Depósitos. Both a univariate and multivariate approach were used in classifying the failed and non-failed groups.

In the univariate approach, the authors found that the mean values for the ratios maintain a logical correspondence (the actual mean values obtained are not mentioned in the study, however). They also found that standard deviations of the failed bank ratios tended to be generally higher. Profitability and liquidity measures were found to be the most significant variables for forecasting failures in a univariate analysis. The cutoff point for the individual ratio was fixed in a heuristic way, by a process of trial and error. The costs of Type I and Type II errors were assumed to be equal.

In the multivariate approach, discriminant analysis was used to develop models using data of j year prior as the development sample ($j= 1,2,3,4,5$) and testing the model on the data for the all the years j . Since the ratios for a bank tend to be correlated from one year to the next, the classification test on the other years does not constitute a true out-of-sample (hold out) test. Some of the classification results presented are nonsensical because if you used data for $j=2$ to develop the model, you can not test it on data of $j=1$ because in real time that information would be non-existent; only $j=3,4$ and 5 would be!

The multiple discriminant analysis produced 3 and 4 variable models for each year prior, resulting in a total of 10 alternative models to choose from. The comparison of the prediction accuracy using univariate analysis and the discriminant analysis showed that univariate analysis actually did better than the discriminant function in the first and the fifth year (Table 5) - a surprising result. Most research using multivariate methods appears to come to the opposite conclusion because it is believed that the interaction or the substitution effects of one variable with others provide better information that if the variables are considered sequentially.

The authors conclude that there is a close balance between univariate ratio approach and the function approach and that both types of analysis can be viewed as complementary.

Table 5

**Overall Accurate Predictions - Comparison of Single Ratios
with Discriminant Functions**

Years	Ratios	Functions
1	90/95%	80/85%
2	75/80	80/85
3	75/80	75/80
4	75/80	75/80
5	80/85	75/80

More rigorous testing using a hold out sample will be needed to confirm that univariate approach has predictive power comparable to the multivariate approach. Coming to this conclusion based solely on original sample test results is premature because of the sample bias in the results.

ITALY

Altman, Marco and Varetto (1994)

This study presents the results of two interesting innovations in the diagnosis of corporate financial distress. The first is the use of a two stage decision process employing two discriminant analysis models to fine tune the process used to grade companies into groups of healthy, vulnerable and unsound companies. The second innovation is the application of neural networks (NN) to solve the same problem. The study is also of interest because of the access of the authors to a large and well-developed database of financial information on over 37,000 companies in Italy, as much as to the pooling of this data by a consortium of banks that have thereupon been able to use the diagnostic system developed for medium and small sized businesses in Italy. After trying out various alternative approaches in neural network modeling the authors conclude that the linear discriminant model compares well relative to neural networks. The main advantages of the discriminant model being its consistency of performance and the modest cost in fine tuning the model. Having said that, the authors state that neural networks continue to hold promise especially in situations where the complexity of the problem can be handled well by the flexibility of NN systems and the capacity to structure them into simple, integrated families.

The study was carried out in the Centrale dei Bilanci (CB) in Turin, Italy. CB is an organization established by the Banca

d'Italia, the Associazione Bancaria Italiana and over forty leading banks and special credit institutions in Italy. CB develops and distributes tools for the members banks to use. One product was a linear discriminant analysis based model that is used in practice to improve credit analyst productivity by pre-selecting the credits and for monitoring the uniformity of the judgments made about businesses by the various branches of the bank.

The first part of the study describes the results of the new release of the system that improves on predictive accuracy by splitting the estimation/classification problems into two steps. In the first step, the two group sample consist of healthy firms on the one hand and unsound and vulnerable companies on the other. "Vulnerable" companies are those that are not at the point being considered "Unsound" but are borderline cases. The second step was to develop another discriminant analysis model to classify the vulnerable companies on the one hand and the unsound companies on the other. Estimation of the model was done based on data 3 years prior to distress and tested on original and control (hold out) sample for 1 and 3 years prior. The results of the tests of the two models are as shown in Table 6.

Table 6

F1 Discriminant Model Results

	Test Period	Healthy Firms	Unsound Firms
Estimation sample 404 companies in each group			
Estimation period	T-3	90.3%	86.4%
Control period	T-1	92.8	96.5
Holdout sample (150 companies in each group)	T-1	90.3	95.1

F2 Discriminant Model Results

	Test Period	Healthy Firms	Unsound Firms
Estimation sample (404 companies in each group)			
Estimation period	T-3	99.0%	60.1%
Control period	T-1	97.8	82.7
Holdout sample (150 companies in each group)	T-1	96.8	81.0

Neural Networks

Neural networks consist of potentially large number of elementary processing units. Every unit is interconnected with other units and each is able to perform relatively simple calculations. The processing behavior of the network is derived from the collective behavior of the units each of which is capable of altering its responses to stimuli from the external environment as well as from the other neurons with which it is linked. Obviously, the change of response is the learning process that the NN goes through as revisions are introduced to the weightings that drive the response. Neural networks can range in complexity from the simple single-layer network to multi-layer networks. In general, the more complex the network, the greater is the promise that it will have a genuine capacity to solve a problem, but greater is the difficulty associated with understanding it's sometimes anomalous behavior. Also more complex networks take longer to train.

The experiment with neural network progressed through four steps:

1. Attempt to replicate the scores generated by multiple discriminant analysis using ratios different from those used in discriminant analysis. The objective in doing so was to verify the network's capacity to do at least as well as discriminant analysis but using a different set of ratios.
2. Train the network using data 3 years prior and test it in 1 year prior data in its ability to separate the healthy and bankrupt companies
3. Attempt to integrate the knowledge implicit in observing the evolution of the various ratios and indicators over time. In other words teach the network to learn from both point-in-time data and trend data.
4. Check the capacity of the network to separate the healthy, vulnerable and unsound companies in the same way as the two stage discriminant analysis models presented earlier.

Results

The best results were obtained with a three-layer network in replicating the scores generated by discriminant analysis. The initial layer of ten neurons, a second layer of four neurons and an output layer consisting of a single neuron (the layering of the network is expressed in shorthand as 10, 4, 1 network). The input consisted of 10 ten financial ratios. The resulting profile after 1000 learning cycles on 808 companies was extremely close to the desired level.

In the second stage (classifying healthy and bankrupt companies) a 15,4 ,1 network provided the best recognition rate, i.e., classification accuracy of 97.7 percent for the healthy companies and 97 percent for the unsound companies. However the authors noted two concerns with the network: it was able to obtain that accuracy using a much higher number of indicators, i.e., fifteen as opposed to nine used by discriminant analysis. Second, its behavior became erratic as the learning progresses -- initially the model makes rapid strides in its capacity to identify the groups but as it moves forward there are often points where its performance actually deteriorates. The led the authors to suggest that neural networks may suffer from "overfitting", a phenomenon encountered with quadratic discriminant functions that do very well in the development sample but fail in hold out testing.

The third stage the authors fed the same ratios used in discriminant analysis to the neural network using the arguments that it is common for analysts and systems to receive a standard information base. The objective was to check the network's

capacity to replicate the knowledge base produced by discriminant analysis, using the same inputs. The results of this, obtained using a 9,5,1 network are as shown in Table 7.

Table 7
Comparison of Classification Rates: Neural Network vs. Linear
Discriminant Analysis

	Neural Network		Linear Discriminant Function (F1)	
Sample size = 404 in each group	Healthy	Unsound	Healthy	Unsound
Estimation T-3 period	89.4%	86.2%	90.3%	86.4
Control T-1 period	91.8	95.3	92.8	96.5

The next experiment involving the synthesis of historical information by the network also produced impressive classification results, but here again, the behavior of the network became at times unexplainable and unacceptable, such as frequent inversion of output values when the inputs were modified uniformly or in limited subsets.

In conclusion, the authors note that while complex networks may produce better classification results, they take longer to train and are more difficult to control in terms of illogical behavior. However, they have shown enough promising features to provide an incentive for better implementation techniques and more creative testing.

Cifarelli, Corielli and Forestieri (1988)

The authors propose a Bayesian variant to the classical discriminant analysis which takes explicit care of the uncertainty with which the parameters of the diagnostic distribution are known when classifications are made. In particular, in "out-of-sample" cases. The classical method uses an estimate density of future observables, whereas the method suggested by the authors uses a predictive density calculated using Bayes theorem.

The sample used to test develop the model came from a large

Italian bank's loan portfolio. Unsound companies were selected among cases of formal declaration of bankruptcy. The sound firm sample was formed by a random selection from the bank loan portfolio, 14 financial ratios descriptive of growth, profitability, productivity, liquidity and financial structure were used. The authors report that the classification accuracy of the Bayesian model is very close to that obtained with different versions of the classical discriminant analysis model.

AUSTRALIA

Australia has certain unique characteristics, with huge development potential (like Brazil) but with an already established industrial base. While the influence of multinational firms is quite important, the local corporate structure is large enough to support a fairly substantial capital market.

Castagna and Matolcsy (1981)

The active financial environment in Australia is a motivation for rigorous individual firm analysis. A series of studies by A. Castagna and Z. Matolcsy (C&M) culminating in their published work (1981) have analyzed corporate failures in Australia and have concluded that there is a strong potential for models like those developed in the United States to assist analysts and managers.

Research Design

One of the difficult requirements for failure analysis found in just about every country in the world outside the United States is assembling a data base of failed companies large enough to perform a reliable discriminant analysis model. Despite a relatively large number of liquidations, Australian data on failed firms are quite restricted. C&M were able to assemble a sample of only 21 industrial companies (the number of firms would have been much larger if mining companies were included). The failure dates spanned the years from 1963 through 1977, with the date determined by the appointment of a liquidator or receiver. An alternative criterion date might have been the time of delisting from the stock exchange or the liquidation/receiver date, whichever comes first. For every failed company in the sample, there is a randomly selected surviving quoted industrial firm from the same period. Industries represented include retailers, manufacturers, builders, and service firms.

Empirical Results

Prior studies by C&M (1975, 1979) reduced the number of potential discriminating variables to 10 which were then analyzed in a linear and quadratic discriminant structure. The authors also attempted to test their results for various *a priori* group membership probabilities. The results suggest that it is difficult to identify a unique model to predict corporate failures and that some specification of user preferences is desirable. Still, they do indicate a 10-variable linear and five-variable quadratic classification models.

As noted, the results of C&M's work are not definitive. For example, if one is concerned with minimizing the misclassification of failed companies, then the linear model using equal priors outperforms all other models tried. This model also had the best overall results, except in the fourth year prior to failure. However, the linear model does not perform better than other models in the classification of surviving companies. A stepwise procedure indicated that a five-variable model did not perform as well as the models based on the ten-ratio set in the overall classification tests. All of their comparisons are based on the Lachenbruch validation tests.

The C&M study does not address prediction accuracy *per se*. All of the tests are on the original sample of 21 firms. In order for the tests to be predictive in nature, their model(s) should be applied to subsequent firm performance in Australia. The authors do note that they expect to monitor their findings on samples of continuing companies listed on the Australian Stock Exchange.

IZAN (1984)

Izan (1984) and Altman and Izan (1983), in a subsequent attempt to address the failure classification problem in Australia, analyzed a larger sample (50-failed firms and an industry-failure-year-matched sample of 50 non-failed firms). Perhaps the most distinctive aspect of this model is the attempt to standardize the ratios by the respective firms' industry medians.

The argument put forward by the author to use industry-relatives is to point to the significant differences that exist among industries of the key financial ratios. As for the counter-argument that some industries are indeed riskier than others, the

author responds by stating that a near-bankrupt situation of any of the industries represented in the study is extremely remote. Having made the argument for using the industry-relatives, the author proceeds to derive the value of this variable by dividing the failed and the non-failed firm's raw ratio by the industry median.

The ten candidate ratios chosen for analysis were the following:

Ordinary earnings/Shareholder funds

Earnings before interest and taxes/Total assets

Earnings after interest and taxes/Total assets

Cash flow/Borrowings

EBIT/Interest

Current assets/Current liabilities

Current assets stocks/Current liabilities-overdrafts

Funded debt/Shareholder funds

Market value of equity/Total liabilities

Book value of equity/market value of equity

The final model was quite similar to the Altman (1968) model. The ratios in the model and their relative contributions are as shown in Table 8.

Table 8

Relative Contribution Tests and Ranks of Variables in the Distress Model

Variable	Univariate F		Standardized Coefficient		Wilk's Lambda		Forward stepwise
	Amount	Rank	Amount	Rank	Amount	Rank	
EBIT/TA	26.4	3	0.79	3	0.23	5	3
EBIT/Interest	49.2	1	0.66	1	0.53	1	1
CA/CL	4.3	5	0.96	5	0.24	4	5
FD/SF	21.6	4	0.82	4	-0.25	3	4
MV/TL	36.9	2	0.72	2	0.44	2	2

The classification accuracy of the models on the development sample one year prior to failure are presented in Table 9.

Table 9
Classification Accuracy of the Industry Relative and the Raw
Ratio Models

Actual Group	No of Cases	Industry Relative Ratios		Raw Ratios	
		Failed	Non-Failed	Failed	Non-Failed
Failed	51	48 (94.1%)	3 (7.8%)	46 (90.2)	5 (9.8%)
Non-Failed	48	5 (10.4%)	43 (89.6%)	5 (10.4%)	43 (89.6%)

The industry relative ratios model showed a Type I accuracy of 94.1%, 75% and 63.5% respectively on data 1, 2 and 3 years prior to failure. Type II accuracy for the same periods was 89.6%, 89.6% and 85.4% respectively. The prediction accuracy on a small secondary sample (hold out) of ten failed firms was 100% one year prior to failure, 70% 2 years prior and 40 percent 3 years prior. In the absence of the corresponding Type II accuracy, this result is difficult to interpret, however.

The author believes that the model is sufficiently robust as to be applicable to a cross-section of firms and industries and appropriate for analyzing firms.

GREECE

Gloubos & Grammatikos (1988)

Companies in regulated economies are often sustained in operation long after they have become economically bankrupt. These causes taxonomic problems for the researcher because to treat such companies as healthy is clearly wrong, while including them in the bankrupt group causes biases because of the difficulties in identifying the date of the bankruptcy. The authors suggest that

estimated models in such economies as Greece may be expected to have a higher degree of misclassification than similar models estimated in market-driven economies. In this study the authors compare four techniques on a "new" sample of healthy and bankrupt firms. The four techniques used are:

- Linear Probability Model (LPM)
- Probit Analysis (PROBIT)
- Logit Analysis (LOGIT)
- Multiple Discriminant Analysis (MDA)

The LPM model is a multiple linear regression model where the dependent variable is a 0-1 variable which is regressed against a set of independent variables. The problems with this approach are that the error terms are hetero-skedastic and their distribution is not normal. Also when the predicted value lies outside the 0-1 range it is difficult to interpret the result. This difficulty is overcome by applying suitable transformations that would restrict the probability predictions to the 0-1 interval. This is done in the PROBIT model where P the conditional probability of failure expressed in terms of a cumulative standard normal distribution function. As to be expected the introduction of the standard normal distribution involved non-linear estimation. The LOGIT model uses a computationally simpler function based on the cumulative logistic probability function. In multiple discriminant analysis, the function is linear or quadratic in the variables.

The sample consisted of 30 Greek industrial firms that went bankrupt during the period 1977-81. Each failed firm was paired with healthy firm of similar size in the same year and from the same industry. Data was gathered for one year prior to bankruptcy and was obtained from various issues of the *Government Gazette*. 17 accounting ratios were used in the analysis and the final models with all four techniques had the same variables. The group statistics for these ratios along with the T-statistics are presented in Table 10.

Table 10

Group Statistics

Variable	Group Mean Bankrupt	Group Mean Non-bankrupt	T-value
Current assets/ current liabilities	0.932	1.579	-3.95
Net working capital/total assets	-0.092	0.196	-5.20
Total debt/total assets	0.813	0.595	5.69
Gross income/total assets	0.077	0.253	-4.51
Gross income/current liabilities	0.106	0.607	6.16

The model results on the development sample are as reproduced in Table 11. It was found that the MDA and LPM have the greater accuracy overall and also in the Type I and Type II categories. The authors note that the MDA model's coefficients for two of the variables had counter-intuitive signs but go on to suggest that because of the interdependencies inherent in a multivariate model, this may be acceptable. The models were tested on 24 new paired sample of bankrupt and healthy firms for the period 1982-85. As to be expected, the classification performance of the models drops of somewhat in the hold out sample as shown in Table 12.

Table 11

Correct Classifications on the Original Sample

A. One year prior to bankruptcy	Overall	Bankrupt	Non-bankrupt
MDA	91.7%	96.7%	86.7%
LPM	91.7	93.3	90.0
PROBIT	85.0	83.3	86.7
LOGIT	86.7	83.3	90.0

Table 12

Correct Classifications on a New Sample

A. One year prior to bankruptcy	Overall	Bankrupt	Non-bankrupt
MDA	66.7%	66.7%	66.7%
LPM	72.9	70.8	75.0
PROBIT	72.9	70.8	75.0
LOGIT	77.1	66.7	87.5
B. Two years prior to bankruptcy			

MDA	71.7	60.9	82.6
LPM	71.7	60.9	82.6
PROBIT	71.7	60.9	82.6
LOGIT	71.7	60.9	82.6
C. Three years prior to bankruptcy			
MDA	75.0	64.3	85.7
LPM	71.4	64.3	78.6
PROBIT	60.7	42.9	78.6
LOGIT	64.3	50.0	78.6

The performance differences among the four models are marginal. The authors recommend using probability models because they are more successful slightly before bankruptcy and their dependent variables can be interpreted directly as probabilities. The fact that the Type I accuracy of these models, which is more critical, is less than Type II accuracy is of some concern, however.

Theodossiou & Papoulias (1988)

The problematic firms in Greece are moribund firms kept alive by government assistance. The assistance is typically provided by banks in the form of external financing under pressure from the government anxious to minimize unemployment that would ensue if these firms are allowed to fail. The 1979 oil crisis, the entrance of Greece into the European Economic Community, and resulting competition, as well as the worldwide recessions in the 1980 brought about the mini-collapse of the industrial sector. Irresponsible lending policies of banks and the improper management of the capital structure by the firms were also, according to the authors, contributing factors. The purpose of the study is to demonstrate, using a corporate failure prediction model developed by the authors, that the prevailing state of problematic firms in Greece could have been anticipated years before the problem became an issue. The models employed are logit, probit and a Bayesian approach to discriminant analysis. In the Bayesian discriminant analysis, the coefficients are identical to those of traditional discriminant analysis. However, the discriminant score is scaled by an intercept in such a way that its distributional assumptions are invariant to either the sample size or the industries. Moreover, this technique is said to be free from the problem of hetero-scedasticity and yield probabilities in the 0-1 interval.

The sample used by the authors contained 33 failed firms and 68 non-failed firms for the year 1983. To adjust the timing of failure for the bankrupt firms kept alive by government

interventions beyond their natural span of existence, the data for such firms was collected as of two years prior to the time their net worth became negative. For others data was gathered for 1 year prior.

The authors found that the performance scores generated by the three models were highly correlated and ranked the problematic firms similarly. Because the models appeared to be equivalent, the authors chose just the probit model for presenting the results. It was found that the probabilities of failure increased for the problematic firms from 0 in 1973-74 to more than 0.5 in the mid-seventies, with complete deterioration of performance of about two thirds of the problematic firms in the sample by 1979.

While there is no doubt that the models anticipated the problematic firms quite well, the results would be more compelling had the authors published the Type I accuracy of the models. A model may have 100 percent Type I accuracy, but if it has 0 Type II accuracy, then it is of no value.

ARGENTINA

Swanson & Tybout (1981)

This paper analyzes the determinants of industrial bankruptcy on Argentina on three levels. First, the importance of macroeconomic variables on the business failures is considered. Real interest rate, credit stock, manufacturing output, real wage rate and the peso exchange rate are regressed on business failures two variables at a time using a multivariate regression with third order polynomial distributed lag terms. Second, sectoral failure rates are examined to determine whether reform policies had a differential effect on highly protected industries. The data is divided into high protection and low protection industries and the differential impact of economic policies is evaluated by adding the degree of protection as a dummy variable in a regression of the number of business failures against the real interest rate and credit stock. The authors then consider the firm-level anatomy of failure by creating probit regression model on a sample of 19 to 22 failures and 190 to 324 survivors with measures of financial structure consisting of cash flow indices, firm financial structure variables, firm size and the degree of protection. The firm failure model was estimated for the pre- post- maxi devaluation period of the Argentinian peso, i.e., 1979-1981 and the period following 1981 respectively.

Following the military coup that ousted Isabel Peron in 1976, Argentina passed through a reform period. The reform started with selective tariff reductions. Soon, contractionary monetary policies and temporary wage and price controls were imposed to combat hyperinflation. In late 1978, an exchange rate regime was introduced. The end result of all these policies led to a maxi devaluation of the peso that threw the economy into a recession. The authors examine the effects of the reform policies with the hope that policy makers will evaluate future policy options in terms of the stress they place on the corporate sector.

Using quarterly data on the macroeconomic variables (24 data points), 10 regressions were estimated using a different combination of two macro variables. Although the business failure rate, rather than the absolute number of business failures would be more appropriate as the dependent variable, the authors did not have the data on the total numbers of businesses in each time period, and therefore they were forced to use the absolute number of failures. The authors also note other the shortcomings: limited size of the data sample, conceptual problems with measuring expected devaluation rates and the distortions in measuring the time of failure by lags in court processing time. The authors conclude, based on the results of the regressions, that of all the factors considered, interest rates and credit stocks are the most important factors in explaining business failures.

The second question examined by the authors is the issue of whether all industries were uniformly affected by the Argentine reforms. The authors' hypothesis is that the high protection industries suffer considerably higher failure levels than the low protection industries when the protection is reduced. Each sub-sample for the study consisted of 12 industries with data for 20 quarters. To account for interindustry difference in the number of firms, the authors included the logarithm of the number of establishments in the industry as an explanatory variable. The authors report statistically significant evidence to support their hypothesis that high protection leads to higher failures when protection is removed.

In order to test their third question, i.e., what are the firm level variables that predict failure, the authors favor the use of a probit regression instead of discriminant analysis because of two stated reasons: that assumptions necessary for statistical inference are typically not satisfied and that the individual influences of the predictors can not be isolated. The criticism of discriminant analysis by the authors is not compelling because the authors appear to tolerate even more serious limitations

caused by the smallness of the sample. Also the standardized discriminant function does show the relative importance of the variables.

The models were estimated for the pre-devaluation period and post-devaluation period. The final model contained ratios with total assets as the best normalizing variable (as opposed to total debt or net worth). The results ratios were the protection index, quick ratio, real financial cost, EBIT, Sales, Debt, Ln(Assets) and Foreign exchange.

In the post-devaluation period, the role of financial costs, foreign currency exposure and firm size become more marked as expected.

In both pre- and post-devaluation periods, the dummy variable for protection has the expected sign but is not statistically significant. The authors conclude based on this outcome, and because sectoral regressions reflect contrasts among firms not listed in stock exchange that higher failure rates for protected firms are concentrated among smaller, privately held firms.

Although by using probit regression the authors could evaluate and present the statistical significance of individual variables, the published statistics (log-likelihood and the Chi-square) do not tell us anything about the classification/misclassification accuracy among fails and non-fails respectively. In addition, the published results are in-sample values. Despite the problems with the data, this article is impressive in the broad sweep of the issues considered in both microeconomic terms and in explicitly modeling trade protection and foreign currency exposure. As we move further into to truly global economy, these variables take on added significance in assessing risk.

BRAZIL

Brazil is an example of an economy where the end result of a series of economic setbacks would put severe pressure on private enterprises. For example, tightening of credit for all firms- especially smaller ones-can jeopardize financial institutions and undermine government efforts to promote economic development. Most observers would agree that action to detect and avoid critical pressures of this type is highly desirable in an economy like Brazil, which has enjoyed extraordinary growth followed by

severe inflation and maxi devaluations. And, as a result of the very recent significant reduction in inflation, banks are now making loans again and are therefore concerned with credit risk issues.

Altman, Baidya, and Ribeiro-Dias (1979)

Altman, Baidya, and Ribeiro-Dias (1979) examined two a priori groups of firms categorized as serious-problem (SP) and no-problem (NP) companies. A small number of variables were then calculated for each observation (firm) in each of the two samples. Data covered the period from one to three annual reporting statements prior to the problem date. The data from one year prior (and the corresponding year for the control sample) were then analyzed through the use of linear discriminant analysis.

The serious-problem firms were defined as those filing formal petitions for court-supervised liquidations, legal reorganizations in bankruptcy (*concordatas*), and out-of-court manifestations of serious problems. In all but two of the 23 serious-problem cases, the problem became manifest during the 30 months from January 1975 to June 1977. Industry categories represented include textiles, furniture, pulp and paper, retail stores, plastics, metallurgy, and others. The average asset size of the serious-problem firms was surprisingly high at 323 million cruzeiros (U.S. \$25-30 million). Therefore, the model, if accurate, has relevance over a wide range of companies in terms of size. The control (or no-problem) sample was actually somewhat smaller.

One or two firms were selected for the control sample from each of the same industrial categories as those represented by the serious-problem group, and data were gathered from the year corresponding to the year prior to the problem date. Since there were more than 30 industrial categories to choose from, the number of firms in each industrial group was often quite small. Whenever possible, privately owned, domestic companies were selected since we felt that a state-owned or multinational affiliation reduced, in general, the possibility of failure.

The classification procedure used in this study is based on the failure model developed in the United States (Altman 1968), with modifications that allow for consideration of Brazilian standards and reporting practices. In this Brazilian study, the same

variables were utilized but X_2 and X_4 were modified. With respect to X_2 , the retained earnings account on U.S. balance sheets reflects the cumulative profits of a firm less any cash dividends paid out and stock dividends. In most instances, the small, young firm will be discriminated against because it has not had time to accumulate its earnings. In Brazil, however, due to different financial reporting practices and adjustments for inflation, there is no exact equivalent to retained earnings. The nearest translation to retained earnings is '*lucros suspetisos*,' which refers to those earnings retained in the business after distribution of dividends. This amount is usually transferred, however, within a short time (perhaps two years) through stock dividends to the account known as capital.

In addition, reserves which were created to adjust for monetary correction on fixed assets and the maintenance of working capital were deducted from profits and thereby decrease those earnings which are reported to be retained in the firm. These reserves, however, increase both the assets, and the firms equity and they too are transferred to capital. In essence, then, that amount of capital which represents funds contributed by the owners of the firm is the only part of equity that is not considered in the Brazilian equivalent to retained earnings. X_2 was calculated as:

$$\frac{\text{(total equity-capital contributed by shareholders (CCS))}}{\text{total assets}}$$

A more precise expression of the numerator would be the cumulative yearly retained earnings plus the cumulative reserves created over the life of the firm, but this information is very difficult to obtain outside the firm and was not available to the authors.

Since most Brazilian firms' equity is not traded, there cannot be a variable which measures the market value of equity (number of shares outstanding times the latest market price). To derive the new values for X_4 , the book value of equity (*patrimonio liquido*) was substituted and divided by the total liabilities. The remaining three variables were not adjusted, although we are aware of the fact that certain financial expenses are also adjusted for inflation in Brazilian accounting.

Empirical Results

The empirical results will be discussed in terms of two separate but quite similar models. The first model, referred to as Z_1 , includes variables X_2 to X_5 (four measures) of the original Z-Score model. Model Z_1 does not include X_1 because the stepwise discriminant program indicated that it did not add any explanatory power to the model and the sign of the coefficient was contrary to intuitive logic. Once again, as so often is found in multivariate failure classification studies, the liquidity variable is not found to be particularly important. The second model, referred to as Z_2 , does not include X_2 , because X_2 is quite difficult to derive with just one set of financial statements and it is similar to X_4 . Model Z_2 can therefore be applied without supplementary data.

The models are as follows:

$$Z_1 = 1.44 + 4.03 X_2 + 2.25 X_3 + 0.14 X_4 + 0.42 X_5$$

$$Z_2 = 1.84 - 0.51 X_1 + 6.23 X_3 + 0.71 X_4 + 0.56 X_5$$

In both cases, the critical cutoff score is zero. That is, any firm with a score greater than zero is classified as having a multivariate profile similar to that of continuing entities and those with a score less than zero are classified as having characteristics similar to those of entities which experienced serious problems.

Results from the two models are essentially identical based on one year prior data. Model Z_1 performed better for Years 2 and 3; therefore, only the results of that model are discussed. Of the 58 firms in the combined two samples, seven are misclassified, yielding an overall accuracy of 88%. The Type I error (that of classifying a serious-problem firm as a continuing entity) was 13% (three out of 23 misclassified) and the Type II error (that of misclassifying a continuing entity) was slightly lower at 11.4% (four of 35). These results are impressive since they indicate that published financial data in Brazil, when correctly interpreted and rigorously analyzed, do indeed possess important information content.

Due to the potential upward bias involved in original sample classification results, further tests of the models were

performed with several types of holdout or validation samples. The accuracy of the SP sample is unchanged after applying the Lachenbruch test. Several replication tests also showed high accuracy levels. Finally, the accuracy of the model is examined as the data become more remote from the serious problem date. The SP sample results, as expected, show a drop in the accuracy of the models. We utilized the weights from the model constructed with Year 1 data and inserted the variable measures for Years 2 and 3 prior to the SP date. Year 2 data provided accuracy of 84.2% (16 of 19 correct). Year 3 data provided lower accuracy of 77.8% (14 of 18 correct) classifications. Therefore, in only four cases were errors observed in classification based on data from three (or more in some cases) years prior to the SP date.

Implications of Results for Brazil

The implications and applications of models designed for assessing the potential for serious financial problems in firms are many. This is especially true in a developing country, where an epidemic of business failures could have drastic effects on the strength of the private sector and on the economy as a whole. Most observers of the Brazilian situation would agree on the merit of preserving an equilibrium among private enterprises, state-owned firms, and multinationals. Such equilibrium would be jeopardized if the domestic private sector were weakened by an escalation of liquidations. If a model such as the one suggested is used to identify potential problems, then in many cases preventive or rehabilitative action can be taken. This should involve a conscious internal effort, by the firms themselves, to prevent critical situations as soon as a potential problem is detected. Besides internal efforts, a program of financial and managerial assistance—more than likely from official external sources—is a potential outcome.

Many economists, including the writers, have argued that significant government assistance for the private sector is an unwise policy except where the system itself is jeopardized. One can rationalize government agencies' attempts to stabilize those industries where a significant public presence or national security is involved, for instance, commercial and savings banks or the steel industry. In developing countries, the distinction between high public interest sectors and the fragile private sector is more difficult to make, and limited early assistance is advocated.

INDIA**Bhatia (1988)**

The author has developed a discriminant analysis model for identifying "sick" companies. Sick companies in India refer to companies that continue to operate or (more accurately are kept in operation even after their economic value is in question) even after incurring losses. The definition used by the Industrial Development Bank of India for sickness is if a company suffers from any of the following ills:

Cash losses for a period of 2 years, or if there is a continuous erosion of net worth, say 50 percent

4 Successive defaults on its debt service obligations

Persistent irregularity in the use the credit lines

Tax payments in arrears for one to two years

The sample consisted of 18 sick and 18 healthy companies all of which are publicly traded. Data used pertained to the period 1976-95. The healthy companies were paired with the sick ones based on the type of product and gross fixed assets. The companies were drawn from the cement, electrical, engineering, glass, paper and steel industries.

The seven ratios in the final discriminant function, along with the standardized discriminant function coefficient are presented in Table 13.

Table 13
Discriminant function coefficients

	Standardized Coefficient	Rank	Unstandardized coefficient
X_1	0.56939	2	1.64621
X_2	0.23186	6	0.03071
X_4	0.34543	4	0.004271
X_5	0.50499	3	0.08169

X ₁	0.64154	1	0.05372
X ₂	0.14993	7	-0.007024
X ₃	0.34498	5	0.006616

X₁ = Current ratio

X₂ = Stock of finished Goods/Sales

X₃ = Profit after Tax/Net worth

X₄ = Interest/Value of Output

X₅ = Cash Flow/Total Debt

X₆ = Working capital Management Ratio

X₇ = Sales/Total Assets

The Type I accuracy was 87.1 cent and the Type II accuracy was 86.6 on the development sample. A hold out test was performed on 20 healthy companies and 28 sick companies. The test results generally validated the efficacy of the model.

IRELAND

In Ireland, Cahill (1981) presents some exploratory work on a small sample of 11 bankrupt, listed companies covering the period from 1970 through 1980. Three primary issues are explored: (1) identification of those ratios which showed a significant deterioration as failure approaches, (2) whether the auditors' reports expressed any reservations or uncertainty about the continuance of the firms as going concerns, and (3) whether there were any other unique aspects of the failed companies' conditions.

Cahill's analysis revealed a number of ratios indicating clear distress signals one year prior to failure. These ratios compared unfavorably with aggregate norms and ratios for the comparable industrial sector. Although several measures continued to show differences in earlier years, the signals were less clear in Year 2 prior and it was difficult to detect strong signals from ratios prior to Year 2.

Only one of the 11 auditors' reports was qualified on the basis of going concern. Five other less serious qualifications were present in the auditor's reports. Cahill speculates that the low frequency of auditor qualifications on a going concern basis was due to auditor reluctance and accounting convention in Ireland as well as their feeling of being part of a "small society." We observed similar circumstances in Australia. Still, according to Cahill, since deterioration was quite apparent, those close to the situation should have been aware of the seriousness and earlier remedial action taken or qualification given.

Unsuccessful merger activity and significant investment and asset expansion financed by debt were the major causes of Irish failures. Several of the firms continued to pay dividends right up to the year prior to failure. On the other hand, only one company actually made payments to unsecured creditors after insolvency, indicating that asset value had deteriorated beyond repair and only then was failure declared.

KOREA

Altman, Kim and Eom (1995)

As a growing and potentially overheated economy, Korea may be following in the footsteps of its neighbor, Japan, which had a period of rapid economic growth only to be followed by increased business failures. For this reason, the authors suggest, that a failure prediction model for Korea is timely, even given the current 1995 robustness of the South Korean economy. In particular, because of the increased deregulation and greater autonomy in decision-making by financial institutions, the availability of predictive models is relevant.

The distress classification model described in this study consists of two versions: the K1 model is applicable for both public and private firms, whereas the K2 model, which uses the market value of equity in one of its ratios, may be used only for publicly traded firms.

Linear discriminant analysis was the technique used in building the model. The sample of failed firms consisted of 34 publicly traded industrial and trading companies with assets ranging from \$13 million to \$296 million. Failure and failure dates were defined based on technical insolvency or liquidation whichever

came first. Technical insolvency is defined as the condition when the credit of a company is no longer accepted. Most of the failures in the sample occurred in 1991-92. It is significant to note that 30 of the 34 distressed firms had their shares publicly traded only since 1988, and 23 of the 30 were listed during the explosion of new IPO listings in 1988 and 1989. For this reason, the results of the model may be of interest to investors and regulators of new issues in the Korean stock market.

Because the non-distressed group of firms tended significantly larger in size on average, the pairing of the healthy firm with the failed firm was based mainly on industry sector grouping. For 34 distressed firms a larger sample of 61 non-failed entities was chosen, with the actual one to one pairing done by random selection from the universe of 61 firms during model building.

The time series analysis of the individual ratio averages revealed that some early warning financial indicators such as book value of equity to total liabilities do not behave in the same way as they do for U.S. firms. This ratio, contrary to expectations, actually improves for failed firms until just before bankruptcy. However the same ratio based on market value behaves as expected. For this reason, the authors have proceeded with two different models: one employing the book equity leverage variable and the other with a market equity variable.

The criteria for selecting the final variable set were as follows:

1. High univariate significance test (see table below)
2. Expected sign for all the model coefficients
3. Original (In-sample) and Hold out (Out-of-sample) test results
4. Reasonable accuracy levels over time.

The K1 model had the following variables:

1. LOG(Total Assets)
2. LOG(Sales/Total assets)
3. Retained Earnings/Total assets

4. Book value of equity/Total liabilities

The classification results on the original sample for the K1 and K2 models are presented in Table 14.

Table 14

Classification Results - Bankrupt Firms
K-1 Model

Years Prior to failure	No of firms	% Correctly Classified
1	34	97.1
2	34	88.2
3	33	69.7
4	32	50.0
5	16	68.8

Classification Results: Non-Bankrupt Firms

Year	No of firms	% Correctly Classified
1988	57	77.2
1989	58	81.0
1990	59	83.1
1991	47	89.4
1992	29	93.1
Total	250	83.6

The K2 model contained the following ratios:

1. LOG(Total Assets)
2. LOG(Sales/Total assets)
3. Retained Earnings/Total assets
4. Market value of equity/Total liabilities

The classification results on the original sample for the K2 models are presented in Table 15.

Table 15

Classification Results: Bankrupt Firms

K-2 Model

Years Prior to failure	No of firms	% Correctly Classified
1	29	96.6
2	23	85.2
3	15	71.4
4	4	40.0
5	3	75.0

Classification Results: Non-Bankrupt Firms

Year	No of firms	% Correctly Classified
1988	40	75.0
1989	51	86.3
1990	57	86.0
1991	47	89.4
1992	29	93.1
Total	224	85.7

The authors note two major limitations of these models. First, because of lack of data, the authors were unable to perform hold out testing. Secondly, the Type II accuracy of 70 percent is perceived to be rather low. Both these limitations will be removed if future tests of the model yield usable predictions.

MALAYSIA**Bidin (1988)**

The New Economic Policy launched by the Malaysian Government in the early 1980's was aimed at increasing and redistributing corporate ownership among the races in that country. The indigenous races in which the Malays form the majority have a disproportionately small share of the corporate wealth. The government has set up a number of public corporations and enterprises to directly involve the indigenous races in terms of ownership and the development of managerial skills. Permodalan Nasional Berhad (PNB) is corporation whose objective is to evaluate, select and acquire shares in corporations with good potential with the intention of ultimately selling them to a unit

trust fund. PNB is thus an investment institution which has developed some expertise in the financial analysis and the monitoring the operations of companies. In 1985 the government entrusted PNB with the additional task of monitoring the performance of all government companies, not just those in PNB's portfolio. This led to the formation CICU, the Central Information Collection Unit, the unit within PNB that performs this function. CICU is charged with the task of identifying companies in distress at an early stage so that the necessary remedial action may be taken by the authorities. A multivariate discriminant analysis model has been built with applicability mainly for manufacturing companies, and also for companies in the transportation and service sector.

The sample consisted of 21 companies known to have been in distress paired with financially sound companies which were entirely Malaysian with business activities in Malaysia. 41 ratios were defined for inclusion in the analysis. Stepwise selection yielded the a discriminant function that had seven variables ranked by the level of contribution to the F statistic as shown in Table 16.

Table 16
Discriminant Function Variables

Variable	R**2	F-Statistic
R1	0.5307	45.230
R2	0.3921	
R3	0.2388	
R4	0.2275	10.898
R5	0.1360	5.665
R6	0.0333	3.181
R7	0.0795	2.935

R1 = Operating Profit/Total Liabilities,

R2 = Current Assets/Current Liabilities,

R3 = EALT/Paid-up Capital,

R4 = Sales/Working Capital,

R5 = Current Assets - Stocks - Current Liabilities/EBIT,

R6 = Total Shareholders' Fund/Total Liabilities,

R7 = Ordinary Shareholders' Fund/Employment of Capital.

The authors present three case studies where the PNB-Score was able to correctly predict the outcome in advance. They also note that the test of the model on over 600 companies showed that the results predicted by the model were found to be relatively consistent with the actual performance of the companies. The model is very sensitive to the liabilities of the company, which is to be expected because failure is most often caused when the companies cash-flows are relative to its fixed debt commitments. The study does not present any information on Type II accuracy. It is also not clear whether the 600 companies tested are all problem companies or they included some healthy ones as well. A revised model is still actively used by PNB.

SINGAPORE

Ta and Seah (1981)

Singapore is a dynamic and growing economy which has attracted a large amount of foreign investment. A business failure prediction model is justified both for preserving Singapore's image as a major financial center and as a way to assist rational investment in Singapore companies by investors and creditors. This study examines 24 financial ratios using linear discriminant function analysis.

The failed firm sample consists of 22 firms with failure dates in the period 1975-83. The failure characteristics of the firms in the sample are as follows: 9% went into receivership, 18% went into creditors' voluntary liquidation, while the rest were involuntary 'winding up' by the order of the court. The matched sample consists of 21 non-failed entities. Only industrial and commercial firms are considered in the samples. The mean asset size of the firms in the sample is \$89.5 million. The data sources for the sample are:

Singapore Registry of Companies and Businesses

Singapore Stock Exchange

National University of Singapore's Financial Database

The discriminant analysis process produced a four variable model consisting of:

Total debt/Equity

Profit before tax/Sales

Profit before tax/Equity

Interest payment/Profit before interest and taxes

The results of the model on the original sample and a validation (hold out) sample are reported in Table 17. The results for the original sample are based on data from one year prior to failure. The validation test results are for 1 and 2 years prior.

Table 17
Summary of results

Original Sample	Original Sample			Holdout Sample		
	Type I accuracy	Type II accuracy	Overall accuracy	Type I accuracy	Type II accuracy	Overall accuracy
Predicti on Horizon						
1 year prior	77.3%	93.5%	86.8%	75.0%	90.5%	86.2%
2-year prior				62.5	85.7	79.3

Although the sample size is relatively small, the results of the model are fairly good, and its performance is assured as quality data is available on a larger number of Singapore companies.

FINLAND

Suominen (1988)

The author employs a multinomial logit model (MNL) to classify firm into two groups: failing and non-failing and to assess relative importance of each financial ratio variable. The second part of the study classifies failed firms further into two groups: firms failed within one year of prediction and firms that failed later. Both models employ the same set of three financial ratios indicative of profitability, liquidity and leverage. The ratios are:

$$\text{PROF} = (\text{Quick flow} - \text{Direct taxes}) / \text{Total assets}, \text{ where Quick flow} = (\text{Net turnover} - \text{Materials and supplies} - \text{Wages})$$

and salaries - Rent and leases - Other expenses + Other revenues)

LIQU = Quick/Total assets, where Quick = (Current assets - Inventories/Current liabilities)

LEVE = Liabilities/Total assets

The author favors the MNL technique, corrected for the constant term, because concerns that the assumptions of equal co-variance matrices and normal distribution of the variables are not usually prevalent or tested when using discriminant analysis. In addition, the coefficients from a MNL model are easily testable. Suominen's sample consists of two sets of data. The first set covers the period 1964-73 and consists of 49 failed firms and 87 healthy firms, both from manufacturing industries. The second set consists of data for a different set of failed and healthy firms covering the period 1981-82.

The PROF ratio was not found to be significant in the models for 1 and 2 years prior to failure. In the 3 years prior model only LEVE was significant. In the 4 years prior model only LIQU was significant. The classification results on the first sample and the second sample are summarized in Table 18. It should be noted that both results are for the sample space and not for hold outs.

Table 18
Classification Accuracy

Years prior	Type I Accuracy %	Type II Accuracy %	Type I Accuracy %	Type II Accuracy %
1	67-71	85-86	65-74	61-65
2	53-57	84	61	70
3	31-33	87-89	65	70
4	26	93-95		

The results of the one year model are comparable to those obtained using discriminant analysis using the same variables. The Type I errors are reported to be fewer in the discriminant model, however.

The purpose behind the second part of the study is not entirely clear. Here the objective is to predict correctly the firms that failed within 1 year of the prediction as distinct from those failed later. The results suggest that the MNL model is able to classify the firms into the two groups with an overall accuracy as indicated in Table 19 for the first and the second sample sets. Type I and Type II accuracy rates could not reported here because this information is not be available in the study.

Table 19
Classification accuracy

	Sample # 1	Sample # 2*
Years of Failure	Accuracy %	Accuracy %
1 versus 2,3,4	73-75	65-70
2 versus 3,4	60-67	57-65
3 versus 4	50-52	

* There are no firms with data extending beyond 3 years prior to failure.

MEXICO

Altman (1995)

Emerging markets credits should be initially analyzed in a manner similar to traditional analysis of U.S. corporates. Once a quantitative risk assessment has emerged out of traditional analysis, it can then be modified for by the qualitative assessments by an analyst for other risks, such as currency risk and industry risk characteristic of the industry itself as well as the firms competitive position in that industry. It is not often possible to build a model specific to an emerging country based on a sample from the country itself because of lack credit experience in that country. To deal with this problem, the author has modified the Altman Z-Score model and renamed the resulting model as the EMS model (Emerging Market Scoring Model).

The process of deriving the rating for a Mexican corporate credit

is as follows:

1. EMS score is calculated and equivalent rating is obtained based on the calibration of the EMS scores with U.S. bond rating equivalents.
2. The company's bond is then analyzed for the issuing firm's vulnerability to servicing its foreign currency denominated debt. This is based on the relationship between the non-local currency revenues minus costs compared to non-local currency expense and non-local currency revenues and non-local currency debt. Then the level of non-local currency cash flow is compared with the debt coming due in the next year. Depending upon the degree of vulnerability seen by the analyzed, the rating is adjusted downward.
3. The rating is further adjusted downward (the credit is seen as riskier) if the company is in an industry considered to be relatively riskier.
4. The rating is further adjusted up or down depending upon the dominance of the firm's position in its industry.
5. If the debt has special features such as collateral or a bona fide guarantor, the rating is adjusted accordingly.

For relative value analysis, the corresponding U.S. corporates' credit spread is added to the sovereign bond's option adjusted spread. Only a handful of the Mexican companies are rated by the rating agencies. Thus the risk assessments such as those provided by EMS are often the only reliable indicators of credit risk to overseas investors in Mexico. The author reports that the rating have proven accurate in anticipating both downgrades (Grupo Synkro in May 1995) and upgrades (Aeromexico in July 1995).

URUGUAY

Pascale (1988)

The economic situation in Uruguay has gone through a major transformation, starting from a period of deep economic

intervention during the period 1950-74 that led to high inflation, low real growth and frequent balance of payments crises. Starting in 1974 there was gradual reduction in the controls for capital flows and the government intervention in economic affairs was reduced and a new tax policy implemented. The change in the economic environment provided a new set of shocks to Uruguayan firms because they had to face new market conditions, and decreased protection. It is in this setting that this model to predict financial problems in firms was developed.

The sample consisted of 44 failed firms (FP's; Financial Problems), and 41 healthy firms (NPs; No problems). The criterion for failure was any one of the following: liquidation, bankruptcy, (forbearance/restructuring) agreement with creditors, arrangements with bank syndicates or other financial backers which did not always involve special formalities but entailed substantial changes in financial structure and cessation of activities owing to financial problems. The firms were in food, beverage, footwear and apparel, leather, chemical and metal products. All the firms selected had no less than 10 workers each, with most firms (both failed and healthy) employing 50 or more workers. Healthy firms were matched with failures based on size and industry, although an exact correspondence was not always possible due to lack of data. Both groups of firms were studied for the period from 1978 to 1982. Of the firms with problems, 77 percent experienced their difficulties in 1980 and 1981, and 11 percent in 1982.

The adjustments performed on the sample data are worth mentioning because normally nominal values of the ratios are used in such studies rather than those based on constant term or inflation-adjusted financials:

1. The data was cross checked with published reports.
2. All amounts were restated in a common currency.
3. Fixed assets were valued in accordance with tax regulations.
4. Current assets and liabilities in local currency were deflated by the wholesale price index applicable to the industry.
5. Investments other than fixed assets were deflated using the general consumer price index.
6. Fixed assets were computed at their value for tax purposes for the first year of data. In subsequent years the adjustments to the value were deflated by the implicit price index for fixed gross investment.

7. Net worth was calculated in constant terms as the difference between assets and liabilities.
8. Sales were deflated using the wholesale price index for the industry.

The variables used in the model along with the means and univariate F statistics are presented in Table 20.

Table 20
Means of the variables and significant tests.

Variable	FP mean	NP mean	F
Asset turnover	1.11932	1.64829	16.39 7
Current ratio	1.02636	2.29415	39.59 4
Changes in working capital	0.03091	0.46927	4.514
Sales/non-bank working capital	2.94295	4.78073	10.43 3
Leverage	1.33432	3.03975	54.26 0
Inventory/bank debt	0.98568	4.58146	21.54 8
Bank debt/total debt	1.68295	2.84097	8.735
Long-term debt/'total debt	0.07455	0.12659	2.912
(Accounts receivable + inventories/accounts payable+spontaneous sources)	3.85841	3.06780	2.070
Inventory turnover	3.90432	7.68439	16.65 6
Rate of return	-0.25068	0.23341	6.414
Sales/debts	1.53454	4.67829	68.24 3
Net earnings/total assets	-0.08705	0.10756	27.05 7

$$F_{1,60}(0.05) = 4.00, \quad F_{1,120}(0.05) = 3.92$$

$$F_{1,60}(0.01) = 7.08, \quad F_{1,120}(0.01) = 6.85$$

The resulting discriminant function using the F value as the criterion to enter contained the following three variables.

Sales/debts

Net earnings /total assets

Long term debt /total debt

The classification accuracy of the model in the original sample was 98 percent for Type I and 85 percent for Type II. In the Lachenbruch test, the corresponding values were 98 percent and 83 percent respectively. The Lachenbruch test (also sometimes called the "jackknife" test) is used to eliminate the sample bias, by estimating the model with one observation held out and then classifying that observation. This process is repeated as many times as there are cases which virtually eliminates any potential bias. The author performed hold out tests by validating the model with random sub-samples. The classification accuracy in the hold out sub-sample ranged from 79 percent to 100 percent. Finally the accuracy of the model was tested on data 2 and 3 years prior to failure. The Type I accuracy for 2 and 3 years prior was 83 percent and the Type II accuracy was 79 percent for 2 years prior and 81 for 3 years prior, indicating that the model had an impressive ability to predict failure.

TURKEY

Unal (1988)

In this study, the author argues in favor of conducting principal component and congruency analysis on the universe of financial ratios in order to reduce the dimensions of the variables selected and minimize multi-collinearity in the discriminant analysis by the use of highly correlated variables. This in turn leads to insufficient discriminating ability and possibly also lack of stability. His research on the Turkish Food sector employs these two techniques to reduce the number of variables that best separate failing and stable firms.

In the second phase, cluster analysis, principal factor analysis and Q factor analysis were conducted to determine the basic financial ratios that will appear in the early warning model. Varimax rotation was applied to the principal factors to obtain a more meaningful interpretation of the principal factors. The basic financial ratios that were obtained were then subjected to discriminant analysis to formulate a failure prediction model for the industry during the period 1979-84.

The failed firm sample consisted of 33 firms. The definition of a failed firm was one that reported continuous losses after a

certain period of time; firms whose capital profitability was below that provided by risk-free Government bonds 2) those firms that had standing debts after the date they were due c) those firms that could not be considered successful because they did not exhibit a positive correlation between the ratios representing risk and profitability respectively. 62 firms registered in the Turkish Capital Market Roster were used in the study. The data comprised of 50 financial ratios.

The author discusses the pros and cons of adjusting the financial numbers for inflation (i.e., use ratios derived from constant dollar data) versus using the nominal amounts. In the end, he used the nominal values because of the limited scope of the research. There are other limitations in a study of this nature, according to the author. The first is the existence of correlation among the financial ratios. This can be addressed through factor analysis. The effect economic change brought about by the business cycle can not be evaluated by looking at data for a narrow band of time. A time series analysis of data from 1979-84 was performed to take account of this problem. To address the question of the distribution of the financial ratios normalcy tests were conducted on the ratios. Although the attempts to normalize through transformations the non-normal ratios proved to be unsuccessful, the normalcy tests did bring about the rejection of outliers that appeared to cause right skewness in the sample data.

After conducting factor analysis to identify principal components, time series analysis to look for ratio stability, and cluster analysis and Q factor analysis to group "like" ratios, the final model was determined.

The ratios satisfying the normalcy conditions, low correlations, and stability were as follows:

- X_1 : Earnings before Income and Tax/Total Assets.
- X_2 : Net Working Capital/Sales.
- X_3 : Long Term Debt/Total Assets.
- X_4 : Total Debt,/Total Assets.
- X_5 : Quick Assets/Inventory.
- X_6 : Quick Assets/Current Debt.

The standardized discriminant function coefficients and the discriminant function are as shown in Table 21. The classification accuracy of the model on the development sample was 97 percent overall. With the same level of accuracy for Type I and II. Tests on data 2 years prior yielded a Type I accuracy of 91 percent and Type II accuracy of 93 percent. No hold-out test results were reported.

Table 21
Discriminant Function Coefficients

Ratio	Coefficient	Coefficient (absolute value of the difference of the means)	The relative importance of the ratio (%)
X ₁	18.11	5.4029	52.04
X ₂	1.64	1.0365	9.98
X ₃	-1.21	0.1078	1.04
X ₄	1.21	0.1806	1.74
X ₅	-0.96	0.3890	3.75
X ₆	5.85	3.2663	31.45

SUMMARY AND A FEW CONCLUSIONS

We have attempted to review and compare a relatively large number of empirical failure classification models from ten countries. Much of the material is derived from little-known sources and as such we hope that the study will stimulate a greater transnational discussion. Indeed, as financial institutions and government agencies in countries such as Canada, the United States, Brazil, France, and England wrestle with the specter of large firm failures in the future, the knowledge that prior work has been done with respect to early warning models may help obviate the consequences or reduce the number of these failures.

We expect that the quality and reliability of models constructed in many of the aforementioned countries to improve (1) as the quality of information on companies is expanded and refined, (2) as the number of business failures increase, thereby providing more data points for empirical analysis, and (3) as researchers and practitioners become more aware of the problems and potential of such models. Where sufficient data do not exist for specific sector models, for instance, manufacturing, retailing, and service firms, the application of industry relative measures, e.g., like Altman and Izan (1981), can perhaps provide a satisfactory framework for meaningful analysis. Of course, this requires that government or private agencies build reliable industry data bases for comparison purposes.

Bibliography

- Abrahams, A. and R. A. I. van Frederiklust, 1976, Discriminant Analysis and the Prediction of Corporate Failure, *European Finance Association 1975 Proceedings*, R. Brealey & G. RRankine, (eds.) Amsterdam: North Holland.
- Altman, E. I., 1968, Financial Ratios, Discriminant Analysis And The Prediction Of Corporate Bankruptcy, *Journal of Finance* 23, no 4. 589-609.
- Altman, E. I., 1993, *Corporate Financial Distress*, John Wiley & Sons, New York
- Altman, E. I., D. W. Kim and Y. H. Eom, 1995, Failure Prediction: Evidence from Korea, *Journal of International Financial Management and Accounting* 6, no 3, 230-249.
- Altman, E. I. and H. Y. Izan, 1983, Identifying Corporate Distress In Australia; An Industry Relative Analysis, *Australian Graduate School of Management*, Sydney.
- Altman, E. I., G. Marco and F. Varetto, 1994, Corporate distress diagnosis: Comparisons using linear discriminant analysis and neural networks (the Italian experience), *Journal of Banking and Finance* 18, 505-529.
- Altman, E. I., R.G. Haldeman and P. Narayanan, 1977, ZETA analysis: A New Model To Identify Bankruptcy Risk Of Corporations, *Journal of Banking and Finance* 1, no. 1, 29-51.
- Altman, E. I., T. Baidya, and L. M. Riberio-Dias, 1979, Assessing Potential Financial Problems of Firms In Brazil, *Journal of International Business Studies*, Fall.
- Altman, E. I. and M. Lavalley, 1981, Business Failure Classification In Canada, *Journal of Business Administration*, Summer.
- Altman, E. I., M. Margaine, M. Schlosser, and P. Vernimmen, 1974, Statistical Credit Analysis In The Textile Industry; A French Experience, *Journal of Financial And Quantitative Analysis*, March.
- Altman, E. I., J. M. Hartzell and M. B. Peck, 1995, Emerging Markets Corporate Bonds Scoring System -- Mexican 1995 Review and 1996 Outlook, New York: Salomon Brothers Inc.
- Appetti, S., 1984, Identifying Unsound Firms in Italy, *Journal of Banking and Finance*, 8, 269.
- Argenti, J., 1983, Predicting Corporate Failure, Institute of Chartered Accountants in English and Wales, *Accountants*

Digest, No. 138.

- Ashton, R. H., 1979, Some Indications of Parameter Sensitivity Research for Judgement Modelling in Accounting., *Accounting Review*, 54, No. 1, 170-179.
- Baetge, J., M. Muss and H. Niehaus, 1988, The Use Of Statistical Analysis To Identify The Financial Strength Of Corporations In Germany, *Studies in Banking & Finance* 7, 183-196.
- Bank of England, 1982, Techniques for Assessing Corporate Financial Strength, *Bank of England Quarterly Bulletin*, June, 221-223.
- Beerman, K., 1976, Possible Ways to Predict Capital Losses With Annual Financial Statements, Dusseldorf.
- Betts, J., 1983, The Identification of Companies at Risk of Financial Failure, *Working Environment Research Group, Report No. 5* (University of Bradford, Bradford).
- Bhatia, U., 1988, Predicting Corporate Sickness In India, *Studies in Banking & Finance* 7, 57-71.
- Bidin, A. R., 1988, The development of a predictive model (PNB-Score) for evaluating performance of companies owned by the Government of Malaysia, *Studies in Banking & Finance* 7, 91-103.
- Bilderbeek, J., 1979, An Empirical Study of the Predictive Ability of Financial Ratios in the Netherlands, *Zeitschrift fur Betriebswirtschaft*, May, No. 5.
- Briones, J. J., J. L. Martin Marin and M. J. Vazquez Cueto, 1988, Forecasting bank failures: The Spanish case, *Studies in Banking & Finance* 7, 127-139.
- Castagna, A. D., and Z. P. Matolcsy, 1982, The Prediction Of Corporate Failure; Testing The Australian Experience. *Australian Journal of Management*, June.
- Cifarelli, D. M., F. Corielli and G. Forestieri, 1988, Business Failure Analysis: A Bayesian Approach With Italian Firm Data, *Studies in Banking & Finance* 7, 73-89.
- Collongues, Y., 1977, Ratios, Financiers et Prevision des failites des Petites et Moyennes Enterprises (Financial ratios and Forecasting of Small and Medium Size Enterprises), *Review Banque*, No. 365.
- Earl, M. J. and D. Marais, 1982, Predicting Corporate Failure in the U. K. Using Discriminant Analysis, *Accounting and Business Research*.
- Fernandez, A. I., 1988, A Spanish model for credit risk classification, *Studies in Banking & Finance* 7, 115-125.

- Gebhardt, G., 1980, *Insolvency Prediction Based On Annual Financial Statements According To The Company Law - An Assessment Of The Reform Of Annual Statements By The Law of 1965 From The View Of External Addresses*, in H. Besters, et al., eds., *Bochumer Beitrage Zur Untennehmungs und Unternehmens-forschung*, Vol 22 (Wiesbaden).
- Ghesquiere, S. and B. Micha, 1983, *L'analyse des defaillances d'entreprises, Rapport de la Journee d'etude des Centrales de Bilans*.
- Gloubos, G. and T. Grammatikos, 1988, *The success of bankruptcy prediction models in Greece*, *Studies in Banking & Finance* 7, 37-46.
- Grammatikos, T. and G. Gloubos, *Predicting Bankruptcy in Industrial Firms in Greece*, *Spoudai* 33, No. 3-4, 421.
- Izan, H.Y., 1984, *Corporate distress in Australia, 1984*, *Journal of Banking and Finance* 8, no 2, 303-320.
- Knight, R. M., 1979, *The Determination Of Failure In Canadian Firms*, *ASA Meetings Of Canada*, Saskatoon, May 28-30, 1979, *University Of Western Ontario Working Paper*, May.
- Ko, C. J., 1982, *A Delineation of Corporate Appraisal Models and Classification of bankruptcy Firms in Japan*, Thesis (New York University).
- Lachenbruch, Peter A., 1967, *An Almost Unbiased Method Of Obtaining Confidence Intervals For The Probability Of Misclassification In Discriminant Analysis*, *Biometrics*, 23.
- Lincoln, M. 1984, *An Empirical Study Of The Usefulness Of Accounting Ratios To Describe Levels Of Insolvency Risk*, *Journal of Banking and Finance*, Vol 8, No. 2, June.
- Mader, F., 1979, *Un Enchantillon d'Enterprises en Difficulte, (A sample of Enterprises in Difficulty)*, *Journee des Centrales der Bilans*.
- Mader, F., 1975, *Les Ratios et l'analyse du risque (Ratios and Analysis of Risk)*, *Analyse Financiere*, Zeme Trimestre.
- Mallo, F., 1976, *FINPLAN-A Model Of Credit Rating In Finland*, *Kansellis - Osake Pakki Bank*, Helsinki.
- Marais, D. A. J., 1979, *A Method of Quantifying Companies Relative Financial Strength*, *Working Paper No. 4* (Bank of England, London).
- Micha, B., 1984, *Analysis of Business Failures in France*, *Journal of Banking & Finance*, Vol 8, No. 2, June, 281.
- Pascale, R., 1988, *A Multivariate Model To Predict Firm Financial Problems: The Case Of Uruguay*, *Studies In Banking & Finance*

7, 171-182.

- Prihti, Aalto, Konkunssin ennustaminen kaseinformation avulla (with English summary; The prediction of bankruptcy with published financial data) *Acta Academiae Oeconomica Helsingiensis A*, No. 13 (Helsinki).
- Papoulias, C. and P. Theodossiou, 1987, Corporate Failure Prediction Models For Greece, Working Paper, Fordham University.
- Schmidt, R., 1984, Early Warning Of Debt Rescheduling, *Journal of Banking & Finance*, Vol. 8, No. 2, June, 357.
- Suominen, S. I., 1988, The prediction of bankruptcy in Finland, *Studies in Banking & Finance* 7, 27-36.
- Swanson, E. and J. Tybout, 1988, Industrial bankruptcy determinants in Argentina, *Studies in Banking & Finance* 7, 1-25.
- Ta, H. P. and L. H. Seah, 1988, Business failure prediction in Singapore, *Studies in Banking & Finance* 7, 105-113.
- Taffler, R. J., 1984, Empirical Models for the Monitoring of U. K. Corporations, *Journal of Banking and Finance*, Vol. 8, No. 2, June 199.
- Taffler, R. J. and H. Tisshaw, 1977, Going, Going, Going- Four Factors Which Predict, *Accountancy*, 50.
- Taffler, R. J., 1982, Forecasting Company Failure in the U. K. Using Discriminant Analysis and Financial Ratios Data, *Journal of Royal Statistical Society*.
- Takahashi, K., Y. Kurokawa and K. Watase, 1984, Corporate bankruptcy prediction in Japan, *Journal of Banking and Finance* 8, no 2, 229-247.
- Tamari, M., 1964, Financial ratios as a means of forecasting bankruptcy, *Economic Review* (Bank of Israel, Jerusalem).
- Theodossiou, P. and C. Papoulias, 1988, Problematic firms in Greece: An evaluation using corporate failure prediction models, *Studies in Banking & Finance* 7, 47-55.
- Unal, T., 1988, An early warning model for predicting firm failure in Turkey, *Studies in Banking & Finance* 7, 141-170.
- van Frederkslust, R., A. I., 1978, Predictability of Corporate Failure, Leiden; *Martinus Nijhoff Social Science Division*.
- von Stein, J. H., 1981, Identifying Endangered Firms, (Hohenheim University, Stuttgart-Hohenheim).
- von Stein, J. H. and W. Ziegler, 1984, The Prognosis And Surveillance Of Risks From Commercial Credit Borrowers,

Journal of Banking and Finance 8, no 2, 249-268.

Webb, L., 1980, Predicting Australian Corporate Failures, Chartered Accountant in Australia, September.

Weibel, P.F., 1973, The Value Of Criteria To Judge Credit Worthiness In The Lending Of Banks, (Bern/Stuttgart)

Weinrich, G., 1978, Predicting Credit Worthiness, Directions of Credit Operations by Risk Class, Galder, Weisbaden.