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# A Review of Bankruptcy Prediction Studies: 1930-Present

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*One of the most well-known bankruptcy prediction models was developed by Altman [1968] using multivariate discriminant analysis. Since Altman's model, a multitude of bankruptcy prediction models have flooded the literature. The primary goal of this paper is to summarize and analyze existing research on bankruptcy prediction studies in order to facilitate more productive future research in this area. This paper traces the literature on bankruptcy prediction from the 1930's, when studies focused on the use of simple ratio analysis to predict future bankruptcy, to present. The authors discuss how bankruptcy prediction studies have evolved, highlighting the different methods, number and variety of factors, and specific uses of models.*

*Analysis of 165 bankruptcy prediction studies published from 1965 to present reveals trends in model development. For example, discriminant analysis was the primary method used to develop models in the 1960's and 1970's. Investigation of model type by decade shows that the primary method began to shift to logit analysis and neural networks in the 1980's and 1990's. The number of factors utilized in models is also analyzed by decade, showing that the average has varied over time but remains around 10 overall.*

*Analysis of accuracy of the models suggests that multivariate discriminant analysis and neural networks are the most promising methods for bankruptcy prediction models. The findings also suggest that higher model accuracy is not guaranteed with a greater number of factors. Some models with two factors are just as capable of accurate prediction as models with 21 factors.*

## INTRODUCTION

The literature on bankruptcy prediction dates back to the 1930's beginning with the initial studies concerning the use of ratio analysis to predict future bankruptcy. Research up to the mid-1960's focused on univariate (single factor/ratio) analysis. The most widely recognized univariate study is that of Beaver [1966]. In 1968, Altman published the first multivariate study, which remains very popular in the literature today.

There is great variety in bankruptcy prediction models from how many and which factors are considered to what methods are employed to develop the model. For example, Altman's [1968] model is a five-factor multivariate discriminant analysis model while Boritz and Kennedy's [1995] model is a 14-factor neural network. The number of factors considered in other models ranges from one to 57 factors. Discriminant analysis was a very popular method for model development in the early stages of bankruptcy prediction. However, advancements and technology have made other methods (including logit analysis, probit analysis, and neural networks) more prominent. Also, some models are more narrowly focused than other models. For instance, Altman [1968] developed his model for manufacturing entities. Edmister [1972] developed a model specifically for prediction of small business failure. Sinkey's [1975] model was aimed at prediction of bank failure. More recently, Wang [2004] developed a model for Internet firms. Other models have been developed for non-U.S. firms. An example is Taffler [1984], who developed models for various types of United Kingdom firms.

This paper continues with a historical summary of bankruptcy prediction studies. The second section of the paper provides brief summaries of the early ratio analysis studies from 1930 to 1965. The third section discusses the evolution of bankruptcy prediction models from 1965 to present. Next, the authors analyze and compare the predictive abilities of the bankruptcy prediction models from 1965 to present. The last section provides concluding remarks and suggestions for future research.

## HISTORICAL SUMMARY OF BANKRUPTCY PREDICTION STUDIES: 1930 TO 1965

The early studies concerning ratio analysis for bankruptcy prediction were univariate studies. These studies focused on individual ratios and sometimes compared ratios of failed companies with those of successful firms. The univariate studies had important implications for future model development as they laid the groundwork for multivariate bankruptcy prediction models. Compared with the next 40 years (1965 to present), there were relatively few studies published in the 1930 to 1965 time period. The most prominent of the early studies are summarized in this section.

In 1930, the Bureau of Business Research (BBR) published a bulletin with results of a study of ratios of failing industrial firms. The study analyzed 24 ratios of 29 firms to determine common characteristics of failing firms. Average ratios were developed based on the ratios of the 29 firms. The ratios of each firm were then compared with the average ratios to show that the failing firms displayed certain similar characteristics or trends. The study found eight ratios that were considered good indicators of the "growing weakness" of a firm. These ratios were Working Capital to Total Assets, Surplus and Reserves to Total Assets, Net Worth to Fixed Assets, Fixed Assets to Total Assets, the Current Ratio, Net Worth to Total Assets, Sales to Total Assets, and Cash to Total Assets. BBR also reported that the Working Capital to Total Assets ratio appeared to be a more valuable indicator than the Current Ratio, despite the fact both were found to be good indicators of weakness.

FitzPatrick [1932] compared 13 ratios of failed and successful firms (19 of each firm status). He found that, in the overwhelming majority of cases, the successful companies displayed favorable ratios while the failed firms had unfavorable ratios when compared with "standard" ratios and ratio trends. FitzPatrick reported that two significant ratios were Net Worth to Debt and Net Profits to Net Worth. Also, FitzPatrick suggested that less importance should be placed on the Current Ratio and Quick Ratio for firms with long-term liabilities.

Smith and Winakor [1935] analyzed ratios of 183 failed firms from a variety of industries in a follow-up study to the BBR's 1930 publication. Smith and Winakor found that Working Capital to Total Assets was a far better predictor of financial problems than both Cash to Total Assets and the Current Ratio. They also found that the Current Assets to Total Assets ratio dropped as the firm approached bankruptcy.

In 1942, Merwin published his study focusing on small manufacturers. He reported that when comparing successful with failing firms, the failing firms displayed signs of weakness as early as four or five years before failure. Also, Merwin found three ratios that were significant indicators of business failure – Net Working Capital to Total Assets, the Current Ratio, and Net Worth to Total Debt.

Chudson [1945] studied patterns of financial structure in an effort to determine if there was a "normal" pattern. He reported that there was no "normal" pattern to financial structure on a general, economy-wide level. However, Chudson [1945, p. 6] found "that within particular industry, size, and profitability groups there is a clustering of ratios." While the study did not specifically address bankruptcy prediction, the results are significant to the development of bankruptcy prediction models. For example, Chudson's findings indicate that models developed for general application across industries may not be as appropriate as industry-specific models.

In 1962, Jackendoff compared the ratios of profitable and unprofitable firms. He reported that the following two ratios are higher for profitable firms than for unprofitable firms: the Current Ratio and Net Working Capital to Total Assets. Also, profitable firms had lower Debt-to-Worth ratios than unprofitable firms.

Four of the studies indicated that Working Capital to Total Assets was an important indicator of financial decline. The Current Ratio was also found to be an important ratio; however, two of the studies indicated that the Current Ratio was not as useful as Working Capital to Total Assets. These early studies laid the groundwork for the studies that followed. As will be discussed in the next section, bankruptcy prediction models began to develop with Beaver's [1966] univariate study and have continued to evolve since then.

## HISTORICAL SUMMARY OF BANKRUPTCY PREDICTION STUDIES: 1965 TO PRESENT

Similar to the early studies discussed in Section II, Beaver [1966] compared the mean values of 30 ratios of 79 failed and 79 non-failed firms in 38 industries. However, Beaver

took his study a step further and tested the individual ratios' predictive abilities in classifying bankrupt and non-bankrupt firms. Beaver found that Net Income to Total Debt had the highest predictive ability (92% accuracy one year prior to failure), followed by Net Income to Sales (91%) and Net Income to Net Worth, Cash Flow to Total Debt, and Cash Flow to Total Assets (each with 90% accuracy). In his suggestions for future research, Beaver indicated the possibility that multiple ratios considered simultaneously may have higher predictive ability than single ratios – and so began the evolution of bankruptcy prediction models. There have been some univariate studies since Beaver's (e.g., [Pinches et al., 1975]; [Chen and Shimerda, 1981]); however, the focus of the paper from this point forward will be on multivariate models.

The first multivariate study was published by Altman [1968]. Altman used multivariate discriminant analysis to develop a five-factor model to predict bankruptcy of manufacturing firms. The "Z-score", as it was called, predicted bankruptcy if the firm's score fell within a certain range. Altman's Z-score model had high predictive ability for the initial sample one year before failure (95% accuracy). However, the model's predictive ability dropped off considerably from there with only 72% accuracy two years before failure, down to 48%, 29%, and 36% accuracy three, four, and five years before failure, respectively. The model's predictive ability when tested on a hold-out sample was 79%.

Since Altman's study, the number and complexity of bankruptcy prediction models have increased dramatically. Appendix A lists 165 bankruptcy prediction studies beginning with Beaver [1966] and Altman [1968] up to present. There was only one other study [Daniel, 1968] besides Beaver's and Altman's that was published in the late 1960's. The numbers climb from there – 28 studies in the 1970's; 53 studies in the 1980's; 70 studies in the 1990's. The early part of this decade has seen 11 studies (2000 to 2004). When more than one method was used to develop models within a study, the study is listed only once in the table with the results for the primary methods used in the study. For example, Mensah [1983] used both multivariate discriminant analysis and logit analysis to develop models in his study. Therefore, the study is listed once in the table with the results of both methods.

The studies in Appendix A are listed first by year of publication, then alphabetically within the year. The table includes the purpose of the model, the type of model, and a summary of reported results. It is important to note that although there are models that have been published in other languages, only models available in English are included in Appendix A. The authors believe that this list is the most thorough compilation of bankruptcy prediction models available.[1]

One issue that needs to be addressed in this review is the definition of "failure" as used in the literature. As noted by Karels and Prakash [1987], there is a diverse set of definitions of failure used for prediction studies. Many studies define failure as actual filing for bankruptcy or liquidation; others define failure as suffering financial stress or an inability to pay financial obligations. Some studies do not provide the definition of failure used for the research. This variance in the definition of failure can make it

difficult to compare models. However, in general, the models included in Appendix A are bankruptcy prediction models – they consider bankruptcy the ultimate "failure."

*Focused Versus Unfocused Models*

As indicated in the footnotes of the table, unless otherwise specified, the models are assumed to have been developed for application to medium to large manufacturing and retail firms (SIC codes 2000 to 3999 and 5000 to 5999). If a model is more narrowly focused, it is indicated in italics in the "purpose of model" column. The most popular type of "focused" model is that used by banks or savings and loan organizations for failure prediction. These 18 models are: Meyer and Pifer [1970]; Sinkey [1975]; Hanweck [1977]; Martin [1977]; Santomero and Vinso [1977]; Pettway and Sinkey [1980]; Rose and Kolari [1985]; Lane et al. [1986]; Pantalone and Platt [1987a, 1987b]; Bell et al. [1990]; Espahbodi [1991]; Tam [1991]; Salchenberger et al. [1992]; Tam and Kiang [1992]; Martin-del-Brio and Serrano-Cinca [1995]; Henebry [1996]; Alam et al. [2000]). The second most popular type of focused model is for manufacturing firm bankruptcy prediction. There are 16 bankruptcy prediction models for manufacturing firms ([Altman, 1968]; [Taffler, 1974, 1977]; [Diamond, 1976]; [Tisshaw, 1976]; [Mensah, 1983]; [Appetiti, 1984]; [Zavgren, 1985]; [Suominen, 1988]; [Theodossiou, 1991]; [Arkaradejdachachai, 1993]; [Tsukuda and Baba, 1994]; [Alici, 1996]; [Sung et al., 1999]; [Zhang et al., 1999]; [Grover, 2003]). Recently, models have been developed for more unique industries, such as hospitality firms [Gao, 1999], computer/software firms [Shah and Murtaza, 2000], casinos [Patterson, 2001] and Internet firms [Wang, 2004]. There is no real pattern to the development of focused models versus general models (i.e., there does not appear to be a trend toward or away from the use of focused models).

*Global Studies*

Most studies have developed models for U.S. firms. However, there are several studies that developed models for non-U.S. firms. These include models for firms in Table 1.

*Model Types*

Since 1968, the primary methods that have been used for model development are multivariate discriminant analysis (MDA), logit analysis, probit analysis, and neural networks.[2] The primary methods for model development used in the studies listed in Appendix A broken down by time period are in Table 2.

The early multivariable models were largely developed using MDA. MDA classifies firms into groups (bankrupt or non-bankrupt) based on each firm's characteristics (ratios/factors). Based on sample observations, coefficients are calculated for each characteristic (ratio). The products of the ratios and their coefficients are summed to give

## Table 1. Models for Non-U.S. Firms

| | |
|---|---|
| Australia | Castanga and Matolcsy [1981]; Izan [1984]; McNamara et al. [1988]; Messier and Hansen [1988] |
| Austria | Rudorfer [1995] |
| Belgium | Gaeremynck and Willekens [2003] |
| Canada | Altman and Levallee [1980]; Springate [1983] |
| Finland | Suominen [1988]; Laitinen [1991]; Luoma and Laitinen [1991]; Kiviluoto [1998] |
| France | Poddig [1995] |
| Germany | Beerman [1976]; Weinrich [1978] |
| Greece | Gloubos and Grammatikos [1988]; Theodossiou [1991]; Dimitras, et al. [1999]; Zopounidis and Doumpos [1999] |
| Italy | Appetiti [1984] |
| Japan | Ko [1982]; Takahashi et al. [1984]; Tsukuda and Baba [1994] |
| Korea | Lee et al. [1996]; Jo et al. [1997]; Sung et al. [1999]; Lee [2001]; |
| Netherlands | Bilderbeek [1977] |
| Singapore | Ta and Seah [1981] |
| Spain | Martin-del-Brio and Serrano-Cinca [1995] |
| Sweden | Skogsvik [1990] |
| Turkey | Unal [1988] |
| UK | Lis [1972]; Taffler [1974, 1977, 1980, 1982]; Tisshaw [1976]; Mason and Harris [1978]; Earl and Marais [1979]; Marais [1980]; Betts and Belhoul [1982, 1983]; El Hennawy and Morris [1983]; Keasey and Watson [1986]; Peel [1987]; Goudie and Meeks [1991]; Wilson et al. [1995]; Alici [1996]; Lennox [1999] |

## Table 2. Model Types

| | Discriminant Analysis | Logit Analysis | Probit Analysis | Neural Networks | Other |
|---|---|---|---|---|---|
| 1960's | 2 | 0 | 0 | 0 | 1 |
| 1970's | 22 | 1 | 1 | 0 | 4 |
| 1980's | 28 | 16 | 3 | 1 | 7 |
| 1990's | 9 | 16 | 3 | 35 | 11 |
| 2000's | 2 | 3 | 0 | 4 | 3 |
| Overall | 63 | 36 | 7 | 40 | 26 |

[Note: Seven studies had more than one method which could be considered "primary"; thus, the number of total studies listed exceeds 165. "Other" methods include linear probability, judgmental, Cusp catastrophe, and Cox proportional hazards models.]

a discriminant score, allowing classification of the firm. Logit analysis and probit analysis began to appear in the late 1970's, but did not overtake MDA in popularity until the late 1980's. Logit analysis and probit analysis take into account the probability that the firm will go bankrupt. The main difference between these two methods is that probit analysis requires non-linear estimation [Dimitras et al., 1996]. In the late 1980's, neural networks began to appear and, in the 1990's, became the primary method used in studies. Neural networks "are designed to emulate the human pattern recognition function" [Anandarajan et al., 2004]. There are several different types of neural network methods; however, the details of these methods are beyond the scope of this paper. Basically, neural networks analyze inputs to find patterns and develop a model capable of a decision-making process. Several sample cases are run during the "training" mode, during which the network "learns" the decision-making process. The "testing" mode is used to validate the neural network model using hold-out sample data.

*Model Factors (variables)*

The number of factors considered in any one study ranges from one to 57. A total of 752 different factors are used in the studies. Six hundred seventy-four (674) of the factors are utilized in only one or two of the studies. Appendix B lists the 42 factors that are considered in five or more of the studies. The factor most common to multiple studies is the ratio of Net Income to Total Assets (Return on Assets), included in 54 studies. The second most common factor is the ratio of Current Assets to Current Liabilities (Current Ratio), found in 51 studies. Six studies ([Coats and Fant, 1992]; [Guan, 1993]; [Nour, 1994]; [Wilson and Sharda, 1994]; [Serrano-Cinca, 1996]; [Lee, 2001]) utilize the five variables included in Altman's [1968] original multivariate model. Generally, any studies that replicated prior studies are not included in the table. However, these six studies are listed because the models were developed using neural networks as opposed to MDA used by Altman. There are at least a dozen other studies not included here that replicate the work done by Altman using MDA or that apply Altman's model or other models to different samples. The number of factors considered in studies broken down by time period is shown in Table 3.

There has been some fluctuation in the range of the number of factors used in studies over the last 40 years; however, the average has remained fairly constant around eight to ten factors.

*Validation Methods*

Jones [1987] pointed out the need for an appropriate validation method when developing and testing bankruptcy prediction models and suggested the use of a hold-out sample to test external validity. Many studies use the Lachenbruch (or "jackknife") method where one observation is withheld from the estimation sample and its classification predicted. This process is repeated until each observation has been withheld

## Table 3. Number of Factors in Studies

|  | Minimum | Maximum | Average (rounded) |
|---|---|---|---|
| 1960's | 5 | 30 | 15 |
| 1970's | 2 | 18 | 8 |
| 1980's | 1 | 47 | 9 |
| 1990's | 2 | 57 | 11 |
| 2000's | 5 | 13 | 8 |
| Overall | 1 | 57 | 10 |

## Table 4. Hold-out Sample Summary

|  | Hold-out sample tested | Hold-out sample not *tested* |
|---|---|---|
| *1960's* | 2 | 1 |
| 1970's | 8 | 20 |
| 1980's | 23* | 29** |
| 1990's | 39 | 31 |
| 2000's | 5 | 6 |
| Overall | 77 | 87 |

* 17 studies were from 1987 or earlier; 6 studies were from 1988-1989.
** 26 studies were from 1987 or earlier; 3 studies were from 1988-1989.
[Note: One study did not provide the details of the sample and whether or not a hold-out sample was used for validation.]

and predicted. The Lachenbruch method is acceptable and often required if the sample size is small. However, a better indication of validity is obtained through the use of a hold-out sample (a separate set of observations). The model is applied to the new set of observations and one is able to acquire a stronger measure of the model's predictive accuracy. It is indicated in the results column of Appendix A if the results presented are based on tests of a hold-out sample. A summary of the use of hold-out samples for the studies by decade is outlined in Table 4.

Based on the information above, it appears that many researchers did not respond to Jones' [1987] suggestion for the use of a hold-out sample to obtain external validation of models. Roughly half of the studies continued to use validation methods other than hold-out testing after the publication of Jones' article.

Table 5. Predictive Ability by Decade and Method

| | Lowest Accuracy | Highest Accuracy | Method(s) used to obtain Highest Accuracy |
|---|---|---|---|
| 1960's | 79% | 92% | Univariate DA [Beaver, 1966] |
| 1970's | 56% | 100% | Linear probability [Meyer and Pifer, 1970] MDA ([Edmister, 1972]; [Santomero and Vinso, 1977]) |
| 1980's | 20% | 100% | MDA ([Marais, 1980]; [Betts and Behoul, 1982]; [El Hennawy and Morris, 1983]; [Izan, 1984]; [Takahashi et al.,1984]; [Frydman et al., 1985]) Recursive partitioning algorithm [Frydman et al., 1985] Neural network [Messier and Hansen, 1988] |
| 1990's | 27% | 100% | Neural networks ([Guan, 1993]; [Tsukuda and Baba, 1994]; [El-Temtamy, 1995]) Judgmental [Koundinya and Puri, 1992] Cumulative sums [Theodossiou, 1993] |
| 2000's | 27% | 100% | MDA [Patterson, 2001] |

## ANALYSIS OF RESULTS

*Model Accuracy*

The bankruptcy prediction literature continually refers to Type I and Type II errors. Type I errors are the misclassification of bankrupt firms as non-bankrupt. Type II errors are the reverse – non-bankrupt firms misclassified as bankrupt firms. It is generally agreed upon that Type I errors are more costly than Type II errors for several reasons including loss of business (audit clients), damage to a firm's reputation, and potential lawsuits/court costs (see for example Koh [1987]). Therefore, the predictive accuracies discussed here refer to the accuracies obtained for bankrupt firms unless the results were not presented separately for bankrupt and non-bankrupt firms. If results were not separately presented, the overall predictive accuracies are discussed.

The predictive abilities of the models vary across time and method. Table 5 shows predictive abilities by method and decade.

## Table 6. Predictive Ability by Model

|  | Lowest Accuracy | Highest Accuracy | Studies which obtained Highest Accuracy |
|---|---|---|---|
| MDA | 32% | 100% | Edmister [1972]; Santomero and Vinso [1977]; Marais [1980]; Betts and Belhoul [1982]; El Hennawy and Morris [1983]; Izan [1984]; Takahashi et al. [1984]; Frydman et al. [1985]; Patterson [2001] |
| Logit analysis | 20% | 98% | Dambolena and Shulman [1988] |
| Probit analysis | 20% | 84% | Skogsvik [1990] |
| Neural networks | 71% | 100% | Messier and Hansen [1988]; Guan [1993]; Tsukuda and Baba [1994]; El-Temtamy [1995] |

It appears that as model development evolved, models were able to predict at the maximum accuracy (100%); however, the low end of the range dropped severely from 79% in the 1960's to as low as 20% in the 1980's. These results do not suggest that newer models are more promising than older models. Considering the primary methods used in model development, the ranges of predictive abilities achieved by models are shown in Table 6.

In numerous studies, MDA and neural network models have provided the highest success rates. Logit analysis also performed quite well in Dambolena and Shulman's [1988] study. However, the method which has had the best accuracy range (71% to 100%) is neural networks. These results imply that MDA and neural networks are the most promising methods for bankruptcy prediction models.

*Prediction Timeframe*

It is also important to consider how far ahead the model is able to accurately predict bankruptcy. Most of the accuracies discussed above are the accuracy rates obtained one year prior to failure. However, some models are able to predict bankruptcy much sooner. For example, Deakin's [1972] model could predict bankruptcy with 96% accuracy two years prior to the failure. Similarly, Dwyer's [1992] model predicted bankruptcy with 97% accuracy three years prior to failure. Better yet, El Hennawy and Morris' [1983] model could accurately predict bankruptcy in 100% of cases up to five years before failure. Clearly, a model that is able to accurately predict bankruptcy earlier becomes more valuable.

*Validation Method*

The predictive ability of a model can also be impacted by whether the results are from tests of an estimation sample or a hold-out sample. Results from an estimation sample tend to be higher because the model is calculated based on that sample. As mentioned previously, a better indication of a model's validity is obtained by testing a hold-out sample. The following nine studies (ten models) obtained 100% classification accuracy based on tests of a *hold-out sample*:

1. Meyer and Pifer [1970] – linear probability
2. Marias [1980] – MDA
3. Izan [1984] – MDA
4. Takahashi et al. [1984] – MDA
5. Frydman et al. [1985] – MDA and recursive partitioning algorithm
6. Messier and Hansen [1988] – neural network
7. Guan [1993] – neural network
8. Theodossiou [1993] – cumulative sums
9. Tsukuda and Baba [1994] – neural network

*Number of Factors (variables)*

One area that appears to have little influence on the predictive abilities of models is the number of factors considered in the model. For the sixteen models that provided 100% classification accuracy, the number of factors ranged from two to 21, broken down as follows in Table 7.

Models that considered as few as two factors had predictive accuracies ranging from 86% to 100%. Models which considered an extremely higher number of factors had comparable accuracies. For example, the model [Jo et al., 1997] that considered 57 factors yielded 86% accuracy and the model [Appetiti, 1984] that considered 47 factors classified firms with 92% accuracy. Therefore, a higher number of factors does not guarantee a higher predictive ability.

As mentioned previously, there have been several studies assessing the usefulness of factors on a univariate basis (e.g., [Pinches et al., 1975]; [Chen and Shimerda, 1981]). Therefore, the authors make no attempt here to analyze the predictive ability or advantages/disadvantages of specific factors.

## CONCLUSIONS

Two prior papers presented comprehensive summaries of bankruptcy prediction research and model development ([Jones, 1987] and [Dimitras et al., 1996]). This paper contributes to the literature by updating Jones' and Dimitras et al.'s efforts and by outlining the considerable body of research concerning the development of bankruptcy

Table 7. Factors Considered & Frequency

| Number of Factors Considered | By x Number of Models |
|:---:|:---:|
| 2 | 1 |
| 3 | 1 |
| 4 | 1 |
| 5 | 4 |
| 7 | 1 |
| 8 | 2 |
| 9 | 1 |
| 11 | 1 |
| 12 | 2 |
| 18 | 1 |
| 21 | 1 |

prediction models. Jones' and Dimitras et al.'s work focused on models for industrial (manufacturing and retail) firms. This paper considers not only industrial models but also models developed for internet firms, casinos, contractors, hospitals, savings and loans, and banks both in the U.S. and internationally. This paper also makes these contributions: (1) summarizes statistics on model attributes, such as the number of factors and method used; (2) presents separately the factors used most frequently in studies; (3) covers predictive accuracies of the models, broken down by decade; (4) compares model accuracies based on the method used for model development; (5) identifies whether or not the studies used a hold-out sample validation; and (6) provides a summary of studies involving non-U.S. firms.

Despite the differences in the bankruptcy prediction models, the empirical tests of most of the models show high predictive ability. This would suggest that the models would be useful to many groups including auditors, managers, lenders, and analysts. However, it appears that bankruptcy prediction models are not utilized in practice on a widespread basis. Further, despite the vast amount of literature and models that have been developed, researchers continue to look for "new and improved" models to predict bankruptcy. With the number of models already available and the apparent limited use in practice, the question is raised: "Why do we continue to develop new and different models for bankruptcy prediction?"

The authors believe that the focus of future research should be on the *use* of existing bankruptcy prediction models as opposed to the development of new models. There are over 150 models available, many of which have been shown to have high predictive ability. Future research should consider how these models can be applied and, if

necessary, refined. Researchers should consider the fact that a large number of factors does not necessarily increase a model's predictive ability. Beaver [1966] was able to predict bankruptcy with 92% accuracy using only one ratio. Jo et al.'s [1997] model that considered 57 factors yielded only an 86% accuracy rate. As Jones [1987, p. 140] points out, "using too many ratios can actually make a model less useful." Lastly, future researchers should attempt to establish a stronger connection between research and practice, similar to other fields such as engineering and medicine. Bankruptcy prediction models could be very useful in practice provided they receive the proper exposure to auditors, managers, lenders, and analysts.

## REFERENCES

Agarwal, A. 1993. Neural networks and their extensions for business decision making. Ph.D. dissertation, Ohio State University.

Aharony, J., C. Jones and I. Swary. 1980. An analysis of risk and return characteristics of corporate bankruptcy using capital market data. *Journal of Finance* 35(4): 1001-1016.

Alam, P., D. Booth, K. Lee and T. Thordarson. 2000. The use of fuzzy clustering algorithm and self-organizing neural networks for identifying potentially failing banks: An experimental study. *Expert Systems with Applications* 18: 185-199.

Alici, Y. 1996. Neural networks in corporate failure prediction: The UK experience. Article in *Neural Networks in Financial Engineering*, A. Refenes, Y. Abu-Mostafa, J. Moddy and A. Weigend (eds.). Singapore: World Scientific, 393-406.

Altman, E. 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. *The Journal of Finance* 23(4): 589-609.

----. 1973. Predicting railroad bankruptcies in America. *Bell Journal of Economics and Management Science* 4(1): 184-211.

----. 1984. The success of business failure prediction models. *Journal of Banking and Finance* 8: 171-198.

----. 2002. *Bankruptcy, Credit Risk and High Yield Junk Bonds*. New York, NY: Blackwell Publishers.

---- and M. Levallee. 1980. Business failure classification in Canada. *Journal of Business Administration* 12(1): 147-164.

---- and B. Loris. 1976. A financial early warning system for over-the-counter broker-dealers. *Journal of Finance* 31(4): 1201-1217.

----, R. Haldeman and P. Narayanan. 1977. Zeta analysis: A new model to identify bankruptcy risk of corporations. *Journal of Banking and Finance* 1(1): 29-51.

Anandarajan, M., P. Lee and A. Anandarajan. 2004. Bankruptcy predication using neural networks. Article in *Business Intelligence Techniques: A Perspective from Accounting and Finance*, M. Anandarajan, A. Anandarajan and C. Srinivasan (eds.). Germany: Springer-Verlag.

Appetiti, A. 1984. Identifying unsound firms in Italy: An attempt to use trend variables.

*Journal of Banking and Finance* 8(2): 269-279.

Arkaradejdachachai, C. 1993. Study of corporate turnaround: Using a probability of bankruptcy. Ph.D. dissertation, University of Missouri.

Aziz, A., D. Emanuel and G. Lawson. 1988. Bankruptcy prediction – An investigation of cash flow based models. *Journal of Management Studies* 25(5): 419-437.

---- and G. Lawson. 1989. Cash flow reporting and financial distress models: Testing of hypotheses. *Financial Management* 18(1): 55-63.

Baldwin, J. and G. Glezen. 1992. Bankruptcy prediction using quarterly financial statement data. *Journal of Accounting, Auditing & Finance* 7(3): 269-285.

Beaver, W. 1966. Financial ratios as predictors of failure. *Journal of Accounting Research* 5: 71-111.

Bell, T., G. Ribar and J. Verchio. 1990. Neural nets versus logistic regression: A comparison of each model's ability to predict commercial bank failures. *Proceedings of the 1990 D&T, University of Kansas Symposium on Auditing Problems.*

Blum, M. 1974. Failing company discriminant analysis. *Journal of Accounting Research* 12(1): 1-25.

Boritz, J. and D. Kennedy. 1995. Effectiveness of neural network types for prediction of business failure. *Expert Systems with Applications* 9(4): 503-512.

Bryant, S. 1996. A case-based reasoning approach to bankruptcy prediction modeling. Ph.D. dissertation, Louisiana State University.

Bukovinsky, D. 1993. Cash flow and cash position measures in the prediction of business failure: An empirical study. Ph.D. dissertation, University of Kentucky.

Bureau of Business Research. 1930. *A Test Analysis of Unsuccessful Industrial Companies.* Bulletin No. 31. Urbana: University of Illinois Press.

Cadden, D. 1991. Neural networks and the mathematics of chaos – an investigation of these methodologies as accurate predictions of corporate bankruptcy. *The First International Conference on Artificial Intelligence Applications of Wall Street.* New York: IEEE Computer Society Press.

Casey, C. 1980. The usefulness of accounting ratios for subjects' predictions of corporate failure: Replication and extensions. *Journal of Accounting Research* 18(2): 603-613.

---- and N. Bartczak. 1985. Using operating cash flow data to predict financial distress: Some extensions. *Journal of Accounting Research* 23(1): 384-401.

Castagna, A. and Z. Matolcsy. 1981. The prediction of corporate failure: Testing the Australian experience. *Australian Journal of Management* 6(1): 23-50.

Chen, K. and T. Shimerda. 1981. An empirical analysis of useful financial ratios. *Financial Management* 10(1): 51-60.

Chudson, W. 1945. *The Pattern of Corporate Financial Structure.* New York: National Bureau of Economic Research.

Clark, C., P. Foster, K. Hogan and G. Webster. 1997. Judgmental approach to forecasting bankruptcy. *Journal of Business Forecasting Methods and Systems* 16(2): 14-18.

Coats, P. and L. Fant. 1992. A neural network approach to forecasting financial distress. *The Journal of Business Forecasting Methods & Systems* 10(4): 9-12.

Dambolena, I. and S. Khoury. 1980. Ratio stability and corporate failure. *The Journal of Finance* 35(4): 1017-1026.

---- and J. Shulman. 1988. *A primary rule for detecting bankruptcy: Watch the cash. Financial Analysts Journal* 44(5): 74-78.

Daniel, T. 1968. *Discriminant analysis for the prediction of business failures.* Ph.D. dissertation, University of Alabama.

Deakin, E. 1972. A discriminant analysis of predictors of business failure. *Journal of Accounting Research* 10(1): 167-179.

---- 1977. Business failure prediction: An empirical analysis. Article in *Financial Crises: Institutions and Markets in a Fragile Environment*, E. Altman and A. Sarmetz (eds.). New York: Wiley-Interscience, 72-98.

Diamond, Jr., H. 1976. Pattern recognition and the detection of corporate failure. Ph.D. dissertation, New York University.

Dimitras, A., S. Zanakis and C. Zopounidis. 1996. A survey of business failures with an emphasis on prediction methods and industrial applications. *European Journal of Operational Research* 90: 487-513.

----, R. Slowinksi, R. Susmaga and C. Zopounidis. 1999. Business failure prediction using rough sets. *European Journal of Operational Research* 114(2): 263-280.

Dwyer, M. 1992. A comparison of statistical techniques and artificial neural network models in corporate bankruptcy prediction. Ph.D. dissertation, University of Wisconsin-Madison.

Edmister, R. 1972. An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial and Quantitative Analysis* 7(2): 1477-1493.

El Hennawy, R. and R. Morris. 1983. The significance of base year in developing failure prediction models. *Journal of Business Finance and Accounting* 10(2): 209-223.

El-Temtamy, O. 1995. Bankruptcy prediction: A comparative study on logit and neural networks. Ph.D. dissertation, Middle Tennessee State University.

Espahbodi, P. 1991. Identification of problem banks and binary choice models. *Journal of Banking and Finance* 15(1): 53-71.

FitzPatrick, P. 1932. A comparison of ratios of successful industrial enterprises with those of failed companies. *The Certified Public Accountant* (October, November, December): 598-605, 656-662, and 727-731, respectively.

Flagg, J., G. Giroux and C. Wiggins Jr. 1991. Predicting corporate bankruptcy using failing firms. *Review of Financial Economics* 1(4): 67-78.

Fletcher, D. and E. Goss. 1993. Forecasting with neural networks: An application using bankruptcy data. *Information & Management* 24: 159-167.

Forsyth, T. 1991. A study of the ability of financial ratios to predict corporate failure and the relationship between bankruptcy model probability assessments and stock market behavior. Ph.D. dissertation, University of Alabama.

Francis, J., H. Hastings and F. Fabozzi. 1983. Bankruptcy as a mathematical catastrophe. *Research in Finance* 4: 63-89.

Frydman, H., E. Altman and D. Kao. 1985. Introducing recursive partitioning for

financial classification: The case of financial distress. *The Journal of Finance* 40(1): 269-291.

Fulmer, J., J. Moon, T. Gavin and J. Erwin. 1984. A bankruptcy classification model for small firms. *The Journal of Commercial Bank Lending* 66(11): 25-37.

Gaeremynck, A. and M. Willekens. 2003. The endogenous relationship between audit-report type and business termination: Evidence on private firms in a non-litigious environment. *Accounting and Business Research* 33(1): 65-79.

Gao, L. 1999. Study of business failure in the hospitality industry from both microeconomic and macroeconomic perspectives. Ph.D. dissertation, University of Nevada-Las Vegas.

Gardiner, L., S. Oswald and J. Jahera. 1996. Prediction of hospital failure – A post PPS analysis. *Hospital & Health Services Administration* 41(4): 441-460.

Gentry, J., P. Newbold and D. Whitford. 1985a. Classifying bankrupt firms with funds flow components. *Journal of Accounting Research* 23(1): 146-160.

----, ---- and ----. 1985b. Predicting bankruptcy: If cash flow's not the bottom line, what is? *Financial Analysts Journal* 41(5): 47-56.

George, C. 1991. The effect of the going-concern audit decision on survival. Ph.D. dissertation, Memphis State University.

Gilbert, L., K. Menon and K. Schwartz. 1990. Predicting bankruptcy for firms in financial distress. *Journal of Business Finance and Accounting* 17(1): 161-171.

Gombola, M., M. Haskins, J. Ketz and D. Williams. 1987. Cash flow in bankruptcy prediction. *Financial Management* 16(4): 55-65.

Goudie, A. and G. Meeks. 1991. The exchange rate and company failure in a macro-micro model of the UK company sector. *Economic Journal* 101(406): 444-457.

Gregory-Allen, R. and G. Henderson Jr. 1991. A brief review of Catastrophe Theory and a test in a corporate failure context. *The Financial Review* 26(2): 127-155.

Grover, J. 2003. Validation of a cash flow model: A non-bankruptcy approach. Ph.D. dissertation, Nova Southeastern University.

Gru, L. 1973. Financial ratios, multiple discriminant analysis and the prediction of small business corporate failure. Ph.D. dissertation, University of Minnesota.

Guan, Q. 1993. Development of optimal network structures for back-propagation-trained neural networks. Ph.D. dissertation, University of Nebraska.

Hanweck, G. 1977. Predicting bank failures. Research Papers in Banking and Financial Economics, Financial Studies Section, Board of Governors of the Federal Reserve System, Washington D.C.

Henebry, K. 1996. Do cash flow variables improve the predictive accuracy of a Cox proportional hazards model for bank failure? *The Quarterly Review of Economics and Finance* 36(3): 395-409.

Hopwood, W., J. McKeown and J. Mutchler. 1989. A test of the incremental explanatory power of opinions qualified for consistency and uncertainty. *The Accounting Review* 64(1): 28-48.

----, ---- and ----. 1994. A reexamination of auditor versus model accuracy within the

context of the going-concern opinion decision. *Contemporary Accounting Research* 10(2): 409-431.

Izan, H. 1984. Corporate distress in Australia. *Journal of Banking and Finance* 8: 303-320.

Jackendoff, N. 1962. *A Study of Published Industry Financial and Operating Ratios.* Philadelphia: Temple University, Bureau of Economic and Business Research.

Jiang, Y. 1993. Bankruptcy prediction – A nonparametric approach. Master's dissertation, Carleton University.

Jo, H., I. Han and H. Lee. 1997. Bankruptcy prediction using case-based reasoning, neural networks, and discriminant analysis. *Expert Systems with Applications* 13(2): 97-108.

Johnsen, T. and R. Melicher. 1994. Predicting corporate bankruptcy and financial distress: Information value added by multinomial logit models. *Journal of Economics and Business* 46(4): 269-286.

Jones, F. 1987. Current techniques in bankruptcy prediction. *Journal of Accounting Literature* 6: 131-164.

Jones, S. and D. Hensher. 2004. Predicting firm financial distress: A mixed logit model. *The Accounting Review* 79(4): 1011-1038.

Kahya, E. and P. Theodossiou. 1999. Predicting corporate financial distress: A time-series CUSUM methodology. *Review of Quantitative Finance and Accounting* 13(4): 323-345.

Karels, G. and A. Prakash. 1987. Multivariate normality and forecasting of business bankruptcy. *Journal of Business Finance & Accounting* 14(4): 573-593.

Keasey, K. and R. Watson. 1986. The prediction of small company failure: Some behavioral evidence for the UK. *Accounting and Business Research* 17: 49-57.

Ketz, F. 1978. The effect of general price-level adjustments on the predictive ability of financial ratios. *Journal of Accounting Research* 16(Supplement): 273-284.

Kiviluoto, K. 1998. Predicting bankruptcies with the Self-Organizing Map. *Neurocomputing* 21(1-3): 191-201.

Koh, H. 1987. Prediction of going-concern status: A probit model for the auditors. Ph.D. dissertation, Virginia Polytechnic Institute and State University.

---- and L. Killough. 1990. The use of multiple discriminant analysis in the assessment of the going-concern status of an audit client. *Journal of Business Finance & Accounting* 17(2): 179-192.

Koster, A., N. Sondak and W. Bourbia. 1990. A business application of artificial neural network systems. *The Journal of Computer Information Systems* 31(2): 3-9.

Laitinen, E. 1991. Financial ratios and different failure processes. *Journal of Business Finance & Accounting* 18(5): 649-673.

Lane, W., S. Looney and J. Wansley. 1986. An application of the Cox proportional hazards model to bank failure. *Journal of Banking and Finance* 10: 511-531.

Lau, A. 1987. A five-state financial distress prediction model. *Journal of Accounting Research* 25(1): 127-138.

Lee, K. 2001. Pattern classification and clustering algorithms with supervised and unsupervised neural networks in financial applications. Ph.D. dissertation, Kent State University.

Lee, K., I. Han and Y. Kwon. 1996. Hybrid neural network models for bankruptcy predictions. *Decision Support Systems* 18(1): 63-72.

Lennox, C. 1999. The accuracy and incremental information content of audit reports in predicting bankruptcy. *Journal of Business Finance & Accounting* 26(5/6): 757-778.

Leshno, M. and Y. Spector. 1996. Neural-network prediction analysis – the bankruptcy case. *Neurocomputing* 10(2): 125-147.

Levitan, A. and J. Knoblett. 1985. Indicators of exceptions to the going concern assumption. *Auditing: A Journal of Practice & Theory* 5(1): 26-39.

Libby, R. 1975. Accounting ratios and the prediction of failure: Some behavioral evidence. *Journal of Accounting Research* 13(1): 150-161.

Lindsay, D. and A. Campbell. 1996. A chaos approach to bankruptcy prediction. *Journal of Applied Business Research* 12(4): 1-9.

Lo, A. 1984. Essays in financial and quantitative economics. Ph.D. dissertation, Harvard University.

Luoma, M. and E. Laitinen. 1991. Survival analysis as a tool for company failure prediction. *Omega* 19(6): 673-678.

Mahmood, M. and E. Lawrence. 1987. A performance analysis of parametric and nonparametric discriminant approaches to business decision making. *Decision Sciences* 18(2): 308-326.

Martin, D. 1977. Early warning of bank failures: A logit regression approach. *Journal of Banking and Finance* 1: 249-276.

Martin-del-Brio, B. and C. Serrano-Cinca. 1995. Self-organizing neural networks: The financial state of Spanish companies. Article in *Neural Network in the Capital Markets*, Refenes (ed.). Chichester: Wiley, 341-357.

McGurr, P. 1996. Failure prediction of retail firms through use of financial ratios. Ph.D. dissertation, Purdue University.

McKee, T. 1995. Predicting bankruptcy via induction. *Journal of Information Technology* 10(1): 26-36.

McNamara, R., N. Cocks and D. Hamilton. 1988. Predicting private company failure. *Accounting and Finance*: 53-64.

Mensah, Y. 1983. The differential bankruptcy predictive ability of specific price level adjustments: Some empirical evidence. *The Accounting Review* 58(2): 228-246.

Merwin, C. 1942. *Financing small corporations in five manufacturing industries, 1926-1936*. New York: National Bureau of Economic Research.

Messier, Jr., W. and J. Hansen. 1988. Inducing rules for expert system development: An example using default and bankruptcy data. *Management Science* 34(12): 1403-1415.

Meyer, P. and H. Pifer. 1970. Prediction of bank failures. *Journal of Finance* 25(4): 853-868.

Moses, D. and S. Liao. 1987. On developing models for failure prediction. *Journal of Commercial Bank Lending* (March): 27-38.

Moyer, R. 1977. Forecasting financial failure: A re-examination. *Financial Management* 6(1): 11-17.

Nittayagasetwat, A. 1994. A test of financial ratios and untransformed financial accounts for predicting bankruptcy. Ph.D. dissertation, University of Mississippi.

Norton, C. and R. Smith. 1979. A comparison of general price level and historical cost financial statements in the prediction of bankruptcy. *The Accounting Review* 54(1): 72-87.

Nour, M. 1994. Improved clustering and classification algorithms for the Kohonen self-organizing neural network. Ph.D. dissertation, Kent State University.

Odom, M. and R. Sharda. 1993. A neural network model for bankruptcy prediction. Article in *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance*. R. Trippi and E. Turban (eds.). Chicago, IL: Probus Publishing Co.

Ohlson, J. 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18(1): 109-131.

Pantalone, C. and M. Platt. 1987a. Predicting commercial bank failure since deregulation. Federal Reserve Bank of Boston *New England Economic Review* (July/August): 37-47.

---- and ----. 1987b. Predicting failure of savings & loan associations. *AREUEA Journal* 15(2): 46-64.

Patterson, D. 2001. Bankruptcy prediction: A model for the casino industry. Ph.D. dissertation, University of Nevada-Las Vegas.

Peel, M. 1987. Timeliness of private company accounts and predicting corporate failure. *Investment Analyst* 83: 23-27.

Pettway, R. and J. Sinkey, Jr.. 1980. Establishing on-site banking examination priorities: An early warning system using accounting and market information. *Journal of Finance* 35(1): 137-150.

Pinches, G., A. Eubank, K. Mingo and J. Caruthers. 1975. The hierarchical classification of financial ratios. *Journal of Business Research* 3(4): 295-310.

Platt, H., M. Platt and J. Pedersen. 1994. Bankruptcy discrimination with real variables. *Journal of Business Finance and Accounting* 21(4): 491-509.

Poddig, T. 1995. Bankruptcy prediction: A comparison with discriminant analysis. Article in *Neural Network in the Capital Markets*, Refenes (ed.). Chichester: Wiley, 311-323.

Raghupathi, W., L. Schkade and B. Raju. 1993. A neural network approach to bankruptcy prediction. Article in *Neural Networks in Finance and Investing: Using Artificial Intelligence to Improve Real-World Performance*, R. Trippi and E. Turban (eds.). Chicago, IL: Probus Publishing Co.

Rahimian, E., S. Singh, T. Thammachote and R. Virmani. 1993. Bankruptcy prediction by neural network. Article in *Neural Networks in Finance and Investing: Using*

*Artificial Intelligence to Improve Real-World Performance*, R. Trippi and E. Turban (eds.). Chicago, IL: Probus Publishing Co.

Rebholz, L. 2002. Bankruptcy as a Cusp Catastrophe. Master of Science thesis, Duquesne University.

Rose, P. and J. Kolari. 1985. Early warning systems as a monitoring device for bank condition. *Quarterly Journal of Business and Economics* 24(1): 43-60.

Rudorfer, G. 1995. Early bankruptcy prediction using neural networks. *APL Quote Quad* 25(4): 171-176.

Rujoub, M., D. Cook and L. Hay. 1995. Using cash flow ratios to predict business failures. *Journal of Managerial Issues* 7(1): 75-90.

Salchenberger, L., E. Cinar and N. Lash. 1992. Neural networks: A new tool for predicting bank failures. *Decision Sciences* 23: 899-916.

Sands, E., G. Springate and T. Var. 1983. Predicting business failures: a Canadian approach. *CGA Magazine* 17: 24-27.

Santomero, A. and J. Vinso. 1977. Estimating the probability of failure for commercial banks and the banking system. *Journal of Banking and Finance* 1(2): 185-205.

Scaggs, M. and P. Crawford. 1986. Altman's bankruptcy model revisited: Can airline bankruptcy be predicted? *Review of Regional Economics and Business* 11(2): 11-16.

Serrano-Cinca, C. 1996. Self organizing neural networks for financial diagnosis. *Decision Support Systems* 17(3): 227-238.

Shah, J. and M. Murtaza. 2000. A neural network based clustering procedure for bankruptcy prediction. *American Business Review* 18(2): 80-86.

Sharma, S. and V. Mahajan. 1980. Early warning indicators of business failure. *Journal of Marketing* 44(4): 80-89.

Shumway, T. 2001. Forecasting bankruptcy more accurately: A simple hazard model. *Journal of Business* 74(1): 101-124.

Sinkey, Jr., J. 1975. A multivariate statistical analysis of the characteristics of problem banks. *Journal of Finance* 30(1): 21-36.

Skogsvik, K. 1990. Current cost accounting ratios as predictors of business failure: The Swedish case. *Journal of Business Finance & Accounting* 17(1): 137-160.

Smith, R. and A. Winakor. 1935. *Changes in Financial Structure of Unsuccessful Industrial Corporations*. Bureau of Business Research, Bulletin No. 51. Urbana: University of Illinois Press.

Sung, T., N. Chang and G. Lee. 1999. Dynamics of modeling in data mining: Interpretive approach to bankruptcy prediction. *Journal of Management Information Systems* 16(1): 63-85.

Taffler, R. 1984. Empirical models for the monitoring of UK corporations. *Journal of Banking and Finance* 8(2): 199-227.

Takahashi, K., Y. Kurokawa and K. Watase. 1984. Corporate bankruptcy prediction in Japan. *Journal of Banking and Finance* 8(2): 229-247.

Tam, K. 1991. Neural network models and the prediction of bankruptcy. *Omega* 19(5): 429-445.

---- and M. Kiang. 1992. Managerial applications of neural networks – the case of bank failure predictions. *Management Science* 38(7): 926-947.

Theodossiou, P. 1991. Alternative models for assessing the financial condition of business in Greece. *Journal of Business Finance & Accounting* 18(5): 697-720.

----. 1993. Predicting shifts in the mean of a multivariate time series process: An application in predicting business failure. *Journal of the American Statistical Association* 88: 441-449.

Tsukuda, J. and S. Baba. 1994. Predicting Japanese corporate bankruptcy in terms of financial date using neural network. *Computers and Industrial Engineering* 27: 445-448.

Unal, T. 1988. An early warning model for predicting firm failure and bankruptcy. *Studies in Banking and Finance* 7: 141.

Wang, B. 2004. Strategy changes and internet firm survival. Ph.D. dissertation, University of Minnesota.

Ward, T. 1994. An empirical study of the incremental predictive ability of Beaver's naïve operating flow measure using four-state ordinal models of financial distress. *Journal of Business Finance & Accounting* 21(4): 547-561.

Wertheim, P. and M. Lynn. 1993. Development of a prediction model for hospital closure using financial accounting data. *Decision Sciences* 24(3): 529-546.

Wilcox, J. 1973. A prediction of business failure using accounting data. *Journal of Accounting Research* 11: 163-179.

Wilson, N., K. Chong and M. Peel. 1995. Neural network simulation and the prediction of corporate outcomes: Some empirical findings. *International Journal of the Economics of Business* 2(1): 31-50.

Wilson, R. and R. Sharda. 1994. Bankruptcy prediction using neural networks. *Decision Support Systems* 11(5): 545-557.

Yang, Z., M. Platt and H. Platt. 1999. Probabilistic neural networks in bankruptcy prediction. *Journal of Business Research* 44: 67-74.

Zavgren, C. 1985. Assessing the vulnerability to failure of American industrial firms: A logistic analysis. *Journal of Business Finance & Accounting* 12(1): 19-45.

Zhang, G., M. Hu, B. Patuwo and D. Indro. 1999. Artificial neural networks in bankruptcy prediction: General framework and cross-validation analysis. *European Journal of Operational Research* 116(1): 16-32.

Zimmer, I. 1980. A lens study of the prediction of corporate failure by bank loan officers. *Journal of Accounting Research* 18(2): 629-636.

Zmijewski, M. 1984. Essays on corporate bankruptcy. Ph.D. dissertation, State University of New York-Buffalo.

Zopounidis, C. and M. Doumpos. 1999. Business failure prediction using the UTADIS multicriteria analysis method. *Journal of the Operational Research Society* 50(11): 1138-1148.

Zordan, A. 1998. Cash-flow ratios as predictors of business failure. Ph.D. dissertation, Nova Southeastern University.

ENDNOTES

[1] Dimitras et al. [1996] provides a review of the literature on failure prediction for industrial firms through the mid-1990's. Their review includes 59 models from 47 studies published in journals.

[2] See Jones [1987] and Dimitras et al. [1996] for more detailed descriptions of the various methods.

[3] Unless otherwise specified, models are assumed to have been developed for application to medium and large manufacturing and retail firms (SIC codes 2000 to 3999 and 5000 to 5999). This "general" application does not include small businesses, financial/insurance/real estate firms (SIC codes 6000 and above), or transportation firms and utilities (SIC codes 4000-4999).

[4] "Hold-out sample" indicates that the results are reported for tests on an external hold-out sample. This does not include tests done using the Lachenbruch method.

[5] Contact the authors for a complete list of factors and considerations included in each study and a complete list of each of the 752 factors that are utilized in the individual studies.

[6] These abbreviations are used in Appendix A, in the order appearing in the table: UDA = Univariate Discriminant Analysis, MDA = Multivariate Discriminant Analysis, LDA = Linear Discriminant Analysis, QDA = Quadratic Discriminant Analysis, LSR = Least Squares Regression, ID3 = Inductive Dichotomizer 3, NN Neural Network, SOFM = Self-organizing Feature Map.

# Appendix A
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | | |
|---|---|---|---|---|---|---|---|---|
| Beaver(1966) | General | UDA/30 | *Model accuracy* – 50% to 92% | | | | | |
| Altman(1968) | *Manufacturing firms* | MDA/5 | *Model accuracy for* hold-out sample – 79% | | | | | |
| Daniel(1968) | General | MDA/10 | Failed firms – 91.8%, Non-failed firms – 100% | | | | | |
| Meyer and Pifer(1970) | *Banks* | LP/18 | Failed banks – 67% to 100%, Non-failed banks – 55% to 89% | | | | | |
| Deakin(1972) | General | MDA/14 | *Year before failure* | *1* | *2* | *3* | *4* | *5* |
| | | | ▪ Failed firms | 77% | 96% | 94% | 91% | 87% |
| | | | ▪ Non-failed firms | 82% | 92% | 82% | 67% | 78% |
| Edmister(1972) | *Small businesses* | LDA/7 | | *Failure* | | *Non-failure* | | |
| | | | z score up to .469 | 80% | | 100% | | |
| | | | .530 and above | 100% | | 86% | | |
| Lis(1972) [Source: Taffler 1984] | *UK firms* | MDA/4 | Failed firms – 88%, Non-failed firms – 83 | | | | | |
| Altman(1973) | *Railroads* | LDA/ | *Model accuracy for* hold-out sample – 83% | | | | | |
| Gru(1973) | *Small businesses* | MDA/5 | Failed firms – 85%, Non-failed firms – 87% | | | | | |
| Wilcox(1973) | General | Binomial/2 | *Year before failure* | *1* | *2* | *3* | *4* | *5* |
| | | | Model accuracy | 94% | 90% | 88% | 90% | 76% |
| Blum(1974) | General | MDA/2 | *Year before failure* | *1* | *2* | *3* | *4* | *5* | *6* |
| | | | Model accuracy (3 year range of data) | 87% | 79% | 72% | 74% | 67% | 57% |
| Taffler(1974)[Source: Taffler 1984] | *UK Mfg.* | MDA/5 | Model accuracy (failed firms) – 60% | | | | | |
| Libby(1975) | General | Judgmental/5 | Model accuracy – 74% on average | | | | | |
| Sinkey Jr. (1975) | *Banks* | MDA/5 | *Year before become problematic* | *1* | *2* | *3* | *4* | |
| | | | ▪ Problem banks | 53.64% | 57.27% | 61.82% | 71.85% | |
| | | | ▪ Non-problem banks | 74.55% | 72.73% | 75.45% | 78.64% | |
| Altman and Loris(1976) | *Broker-dealers* | LDA/15 | Failed firms – 66.7% to 87.5%, Non-failed firms – 58.3% to 85.0% | | | | | |
| Beerman(1976)[Source: Altman 1984] | *German firms* | LDA/10 | *Year before become problematic* | *1* | *2* | *3* | *4* | |
| | | | Model accuracy | 90.5% | 81.0% | 71.4% | 61.9% | |

Appendix A (continued)

Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | | | | |
|-------|------------|---------------|---------------------------------------|---|---|---|---|---|
| Diamond Jr. (1976) | *Manufacturing firms* | Opt discriminant plane (8 factors) | *Year before failure* | 1 | 2 | 3 | | |
| | | | • Failing firms | 97.3% | 78.7% | 80.0% | | |
| | | | • Non-failing firms | 90.7% | 85.3% | 80.0% | | |
| Tisshaw(1976) [Source: Taffler 1984] | *Privately owned UK manufacturing firms* | MDA/5 | *Model accuracy:* Failing firms – 97%, Non-failing firms – 97% | | | | | |
| Altman, Haldeman and Narayanan(1977) | General | LDA/7 | *Year before failure* | 1 | 2 | 3 | 4 | 5 |
| | | | • Bankrupt firms | 92.5% | 84.9% | 76.5% | 61.7% | 62.8% |
| | | | • Non-bankrupt firms | 91.4% | 91.4% | 91.4% | 93.0% | 84.0% |
| Bilderbeek(1977) [Source: Altman 1984] | *The Netherlands firms* | Step-wise DA/5 | Ranges from 70-80% for 1 year prior to bankruptcy, stable over a 5 year period prior to failure | | | | | |
| Deakin(1977) | General | MDA/5 | *Model accuracy for* hold-out sample *of failed firms:*83% correctly classified as failing, 2% incorrectly classified as non-failing, 15% not classified by model | | | | | |
| Hanweck(1977) | *Banks* | Probit analysis (6 factors) | *Model accuracy for* hold-out sample*:* • Failed banks – 67% • Non-failed banks – 99% | | | | | |
| Martin(1977 | *Bank* | Logit analysis/4 | *Year before failure* | 1 | 2 | 3 | 4 | 5 | 6 |
| | | | • Failed banks | 91.3% | 83.3% | 92.3% | 80.0% | 58.3% | 41.7% |
| | | | • Non-failed banks | 91.1% | 90.3% | 87.4% | 87.8% | 85.6% | 82.2% |
| | | LDA/4 | • Failed banks | 82.6% | 83.3% | 69.2% | 80.0% | 58.3% | 41.7% |
| | | | • Non-failed banks | 96.2% | 93.2% | 95.7% | 90.6% | 88.6% | 88.7% |
| | | QDA/4 | • Failed banks | 91.3% | 88.9% | 76.9% | 90.0% | 66.7% | 66.7% |
| | | | • Non-failed banks | 92.0% | 91.1% | 93.2% | 90.2% | 89.8% | 78.9% |
| Moyer(1977) | General | MDA/9 | *Year before failure* | 1 | 2 | 3 | | |
| | | | • Failing firms | 89% | 89% | 89% | | |
| | | | • Non-failing firms | 82% | 78% | 41% | | |
| Santomero and Vinso(1977) | *Banks* | MDA/2 | Risky banks – 27% to 100%, Non-failing firms – 11% to 97% | | | | | |

## Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | |
|-------|-------------|-----------------|-------------------|---|---|---|---|
| Taffler(1977) [Source: Taffler 1984] | *UK manufacturing firms* | MDA/4 | • Failing firms – 98%<br>• Non-failing firms – 100% | | | | |
| Ketz(1978) | General | MDA/16 | Failed firms – 27% to 56%, Non-failed firms – 93% to 97% | | | | |
| Mason & Harris(1978) [Source: Taffler 1984] | *UK construction firms* | MDA/6 | Model accuracy for *hold-out sample* (failed firms) – 64% | | | | |
| Weinrich(1978) [Source: Altman 1984] | *Small & intermediate size German firms* | Non-para linear discrim analysis (factors unknown) | *Year before failure*<br>Model accuracy | 2<br>89.0% | 3<br>84.3% | 4<br>78.1% | |
| Earl and Marais(1979) [Source: Taffler 1984] | *UK manufacturing & distribution firms* | MDA/4 | *Year before failure*<br>• Failing firms<br>• Non-failing firms | 1<br>97%<br>91% | 2<br>92%<br>83% | | |
| Norton and Smith(1979) | General | MDA/11 | Bankrupt firms – 73.3% to 85.2%, Non-bankrupt firms – 60.0% to 96.7% | | | | |
| Aharony, Jones,Swary(1980 | General | LSR/1 | Bankrupt firms – 51.4% to 91.1%, Non-bankrupt firms – 46.2% to 71.2% | | | | |
| Altman and Levallee(1980) | *Canadian firms* | LDA/5 | Bankrupt firms – 70.0% to 94.1%, Non-bankrupt firms – 61.5% to 90% | | | | |
| Casey(1980) | General | Judgmental/6 | Bankrupt firms – 27%, Non-bankrupt firms – 87% | | | | |
| Dambolena & Khoury(1980) | General | LDA/21 | Failed firms – 66% to 91%,, Non-failed firms – 75% to 100% | | | | |
| Marais(1980) [Source: Taffler 1984] | *UK manufacturing & distribution firms* | MDA/4 | *Hold-out sample* (failed firms) – 100% | | | | |
| Ohlson(1980) | General | Logit/9 | *Year before failure*<br>Model accuracy<br>* With 2 additional factors: Cash flow from operations / Sales; Intangibles + deferred assets / Total assets | 1<br>96% | 2<br>96% | 1 or 2<br>93% | 1*<br>96.3% |
| Pettway & Sinkey Jr. (1980) | *Banks* | MDA/4 | Failed banks – 75% to 92%, Non-failed banks – 67% to 100% | | | | |
| Raja, & Goureia(1980) [Source: Casey and Bartczak 1985] | General | LDA/9 | "Problem" firms – 79%, "Growth" firms – 65%<br>Cash flow / Total debt most significant univariate discriminator | | | | |
| Sharma and Mahajan(1980) | *Retail firms* | MDA/2 | *Year before failure*<br>Model accuracy | 1<br>92% | 2<br>78% | 3<br>74% | 4<br>73% / 5<br>77% |
| Taffler(1980) [Source: Taffler 1984 | *UK distribution firms* | MDA/4 | Failed firms – 96%, Non-failed firms – 100% | | | | |

Appendix A (continued)

Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | | |
|-------|-------------|----------------|-------------------|---|---|---|
| Zimmer(1980) | General | Judgmental/5 | *Participant's confidence level* | *Very confident* | *Confident* | *Not very confident* |
| | | | ▪ Failed firms | 89.7% | 78.9% | 74.6% |
| | | | ▪ Non-failed firms | 58.0% | 78.0% | 83.6% |
| Castanga & Matolcsy(1981) | *Australian firms* | MDA/10 | Bankrupt firms – 0% to 90%, Non-bankrupt firms – 76% to 100% | | | |
| Ta &Seah(1981) [Source: Altman 2002] | *Singapore firms* | LDA/4 | *Year before failure* | *1* | *2* | |
| | | | ▪ Bankrupt firms | 75.0% | 62.5% | |
| | | | ▪ Non-bankrupt firms | 90.5% | 85.7% | |
| Betts & Belhoul(1982) [Source: Taffler 1984] | *UK firms* | MDA/5 | Failed firms – 100%, Non-failed firms – 96% | | | |
| Ko(1982) [Source: Altman 1984] | *Japanese firms* | LDA/5 | Model accuracy – 82.9% | | | |
| Taffler(1982) [Source: Taffler 1984] | *UK private Mfg & Construction firms* | MDA/4 | Failed firms – 95%, Non-failed firms – 96% | | | |
| Betts &Belhoul(1983) [Source: Taffler 1984] | *UK firms* | MDA/7 | Failed firms – 96%, Non-failed firms – 96% | | | |
| El Hennway, Morris (1983) | *UK Mfg, constr, dist* | MDA/8 | Failed firms – 94% to 100%, Non-failed firms – 78% to 100% | | | |
| Francis, Hastings& Fabozzi (1983) | General | Cusp catastrophe (2 factors) | Model not empirically tested | | | |
| Mensah(1983) | *Manufacturing firms* | MDA/32 Logit/32 | Bankrupt firms – 18% to 55%, Non-bankrupt firms – 80% to 86% <br> Bankrupt Firms <br> SPL model outperforms HC model at probability of non-failure cutoff .41-.875 <br> HC model outperforms SPL model at probability of non-failure cutoff .125-41 <br> Combined model outperforms individual models at all cutoff .25 to 1 | | | |
| Springate(1983) [Source: Sands, Springate & Var 1983] | *Canadian firms* | MDA/4 | Failed firms – 90%, Non-failed firms – 95% | | | |
| Appetiti(1984) | *Italian manufacturing firms* | UDA & MDA/47 | Unsound firms – 24% to 92%, Sound firms – 24% to 84% | | | |
| Fulmer, Moon, Gavin and Erwin(1984) | *Small firms* | MDA/9 | *Year before failure* | *1* | *2* | |
| | | | ▪ Bankrupt firms | 96% | 70% | |
| | | | ▪ Non-bankrupt firms | 100% | 93% | |
| Izan(1984) | *Australian firms* | MDA/5 | *Year before failure* | *1* | *2* | *3* |
| | | | | 100% | 70% | 40% |

# Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] |
|---|---|---|---|
| Lo(1984) | General | Logit/6 | Results of model's predictive ability not presented |
| Takahashi, Kurokawa and Watase(1984) | *Japanese firms* | MDA/8 | Bankrupt firms – 100%, Non-bankrupt firms – 53% to 75% |
| Zmijewski(1984) | General | Probit/6 | Bankrupt firms – 20.0%, Non-bankrupt firms – 99.5% |
| Casey and Bartczak(1985) | General | MDA/9 | Bankrupt firms – 57% to 90%, Non-bankrupt firms – 47% to 87% |
| | | Logit/9 | Bankrupt firms – 13% to 63%, Non-bankrupt firms – 95% to 98% |
| Frydman, Altman and Kao (1985) | General  Note: Model accuracy based on application to 4 bankrupt firms. | Recursive partitioning algorithm (RPA) (6 of 12 factors) | *Year before failure* — 1, 2, 3, 4, 5; Model accuracy for *hold-out sample* — 100%, 100%, 50%, 50%, 75% |
| | | MDA/10 of 12 | Model accuracy for *hold-out sample* — 100%, 75%, 50%, 25%, 75% |
| Gentry, Newbold and Whitford(1985a, 1985b) | General | Logit/8  Probit/8 | *Year before failure* — 1 / 3 (means); Weak firms 69.6% / 78.2%; Non-weak firms 73.9% / 69.6%; Failed firms 78.8% / 78.8%; Non-failed firms 87.9% / 78.8% |
| Levitan and Knoblett(1985) | General | MDA/26 | *Year before failure* — 1, 2, 3; Model accuracy 95%, 91%, 83%; Going concern opinion 84%, 65%, 54%; Going concern opinion, only bankrupt firms 66%27%, 9% |
| Rose and Kolari(1985) | *Banks* | MDA/23 | *Year before failure* — 1, 2, 3, 4, 5, 6; Failed banks 76%, 77%, 69%, 62%, 62%, 72%; Non-failed banks 69%, 71%, 66%, 59%, 67%, 69% |
| Zavgren(1985) | *Manufacturing firms* | Logit analysis (7 factors) | *Year before failure* — 1, 2, 3, 4, 5; Model accuracy for *hold-out sample* 69%, 69%, 69%, 69%, 69% |
| Keasey and Watson(1986) | *Small UK firms* | Judgmental/6 | Failed firms – 62.8% to 66.1%, Non-failed firms – 66.7% to 68.3% |
| | | MDA/5 | Failed firms – 70.0%, Non-failed firms – 80.0% |

## Appendix A (continue)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | |
|---|---|---|---|---|---|---|---|
| Lane, Looney and Wansley (1986) | *Banks* | Proportional hazard/7 | *Year before failure* | *1 (4 of 7 factors)* | | *2 (6 of 7 factors)* | |
| | | | • Failed banks | 97% | | 89% | |
| | | | • Non failed banks | 74% | | 67% | |
| | | LDA/7 | • Failed banks | 92% | | 61% | |
| | | | • Non-failed banks | 88% | | 78% | |
| | | QDA/7) | • Failed banks | 87% | | 74% | |
| | | | • Non-failed banks | 86% | | 61% | |
| Scaggs and Crawford(1986) | *Airlines* | MDA/5 | Bankrupt firms – predicted accurately at least 3 years before bankruptcy Non-bankrupt firms – predicted accurately for each of the five years before bankruptcy for 4 of the 9 non-bankrupt firms | | | | |
| Gombola, Haskins, Ketz and Williams(1987) | General | MDA/9 | *Year before failure* | *1* | *2* | *3* | *4* |
| | | | Model accuracy (over all years) | 85-89% | 67-70% | 73-78% | 70-76% |
| Karels and Prakash(1987) | General | MDA/5 | Bankrupt firms – 54.5%, Non-bankrupt firms – 96.0% | | | | |
| Lau(1987) | General | Logit/10 | *Model accuracy (converted from probabilistic predictions) for hold-out sample:* • Financially stable firms – 85.4% to 93.7% • Firms omitting or reducing dividend payments – 10% to 50% • Firms with technical default/default on loans – 33.3% to 66.7% • Firms under Bankruptcy Act protection – 10% to 20% • Bankrupt or liquidating firms – 20% | | | | |
| Mahmood and Lawrence (1987) | General | LDA/13 | Bankrupt firms – 28.6% to 73.8%, Non-bankrupt firms – 90% to 96.6% | | | | |
| | | QDA/13 | Bankrupt firms – 42.9% to 73.8%, Non-bankrupt firms – 58.9% to 92.2% | | | | |
| | | Logit/13 | Bankrupt firms | 52.4% 45.2% | 31.0% | 54.8% | 34.1% |
| | | | Non-bankrupt firms | 92.7% 94.7% | 91.7% | 91.7% | 92.7% |
| | | Linear Prog/13 | Bankrupt firms | 40.5% 59.5% | 45.2% | 64.3% | 35.6% |
| | | | Non-bankrupt firms | 76.0% 72.6% | 79.6% | 66.1% | 69.8% |
| Moses and Liao(1987) | *Small, private govt contractors* | MDA/3 | Bankrupt firms – 85%, Non-bankrupt firms – 73% | | | | |
| Pantalone and Platt(1987a) | *Banks* | Logit /5 | Failed banks – 86.7%, Non-failed banks – 83.4% | | | | |
| Pantalone and Platt(1987b) | *S&L associations* | MDA/9 | Failed S&Ls – 85.71%, Non-failed S&Ls – 96.00% | | | | |

## Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | | | | |
|---|---|---|---|---|---|---|---|---|
| Peel(1987) | *Private UK firms* | Logit analysis (8 factors) | *Model number (number of factors)* | *1 (1)* | *3 (4)* | *4(5)* | *5 (4)* | *6 (5)* |
| | | | ▪ Failed firms | 67% | 75% | 92% | 75% | 92% |
| | | | ▪ Non-failed firms | 79% | 83% | 88% | 83% | 88% |
| Aziz, Emanuel and Lawson (1988) | General | LDA/6 | *Year before failure* | | | | | |
| | | | Model accuracy | *1* | *2* | *3* | *4* | *5* |
| | | | | 88.8% | 80.6% | 72.5% | 77.1% | 80.9% |
| | | Logit/6 | Bankrupt firms | | | | | |
| | | | ▪ Non-bankrupt firms | 85.7% | 85.7% | 79.6% | 81.3% | 84.8% |
| Dambolena &Shulman,1988 | General | Logit/14 | Failed firms – 84% to 98%, Non-failed firms – 68% to 86% | 98.0% | 83.7% | 77.6% | 79.2% | 76.7% |
| Gloubos and Grammatikos (1988) [Source: Altman 2002] | *Greek firms* | Linear probability model/5 | *Year before failure* | | | | | |
| | | | ▪ Bankrupt firms | | *1* | *2* | *3* | |
| | | | ▪ Non-bankrupt firms | | 70.8% | 60.9% | 64.3% | |
| | | Probit/5 | | | 75.0% | 82.6% | 78.6% | |
| | | | ▪ Bankrupt firms | | | | | |
| | | Logit/5 | | | 70.8% | 60.9% | 42.9% | |
| | | | ▪ Non-bankrupt firms | | | | | |
| | | MDA/5 | ▪ Bankrupt firms | | 75.0% | 82.6% | 78.6% | |
| | | | ▪ Non-bankrupt firms | | 66.7% | 60.9% | 50.0% | |
| | | | ▪ Bankrupt firms | | 87.5% | 82.6% | 78.6% | |
| | | | ▪ Non-bankrupt firms | | 66.7% | 60.9% | 64.3% | |
| McNamara, Cocks and Hamilton(1988) | *Private Australian firms* | MDA/6 | Bankrupt firms – 86.4%, Non-bankrupt firms – 83.3% | | 66.7% | 82.6% | 85.7% | |
| Messier Jr. and Hansen (1988) | *Australian land development firms* | Inductive Dichotomizer 3 /3 | Model correctly classifies 100% of hold-out sample (12 bankrupt, 4 non-bankrupt) | | | | | |
| Suominen (1988) [Source: Altman 2002] | *Finnish manufacturing firms* | Logit analysis (3 factors) | *Year before failure* *Model accuracy:* | *1* | *2* | *3* | *4* | |
| | | | ▪ Bankrupt firms | 67-71% | 53-57% | 31-33% | 26% | |
| | | | ▪ Non-bankrupt firms | 85-86% | 84% | 87-89% | 93-95% | |

Appendix A (continued)

Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | | | |
|-------|-------------|----------------|----------------|---|---|---|---|---|---|
| Unal (1988) | General | Multivariate discriminant analysis (6 factors) | *Model accuracy:* | | | | | | |
| | *Turkish food sector firms* | | • Failing firms – 91% | | | | | | |
| | | | • Non-failing firms – 93% | | | | | | |
| Aziz and Lawson (1989) | General | Logit analysis (10 factors) | *Model accuracy for* hold-out sample: | | | | | | |
| | | | • Bankrupt firms – 53.9% to 92.3% | | | | | | |
| | | | • Non-bankrupt firms – 70.2% to 79.1% | | | | | | |
| Hopwood, McKeown and Mutchler (1989) | General | Logit analysis (7 factors) | *Model accuracy (misclassification costs ratio 50:1) for* hold-out sample: | | | | | | |
| | | | • Bankrupt firms – 3.1% to 62.5% | | | | | | |
| | | | • Non-bankrupt firms – 87.5% to 100% | | | | | | |
| Bell, Ribar and Verchio (1990) | *Commercial banks* | Logit/8 | Bankrupt firms – 69.5%, Non-bankrupt firms – 97.3% | | | | | | |
| | | NN/11 | Neural network model outperforms logit model up to Type II error=20% | | | | | | |
| | | | Largest difference in models is where Type II error=5% | | | | | | |
| | | | Only three spots where difference between models is more than 3 predictions | | | | | | |
| Gilbert, Menon and Schwartz (1990) | General | Logit/6 | Bankrupt firms – 29.2% to 62.5%, Non-bankrupt firms – 90.6% to 97.9% | | | | | | |
| Koh and Killough(1990) | General | MDA/4 | Failed firms – 78.6%, Non-failed firms – 88.6% | | | | | | |
| Koster, Sondak and Bourbia (1990) | General | NN/2 | Model accuracy – 65.9% to 85.7% | | | | | | |
| Skogsvik (1990) | *Swedish mining & manufacturing firms* | Probit/17 | *Year before failure* | *1* | *2* | *3* | *4* | *5* | *6* |
| | | | *Model accuracy:* | | | | | | |
| | | | • Current cost ratios | 84.0% | 77.2% | 75.2% | 74.1% | 73.0% | 71.2% |
| | | | • Historical cost ratios | 83.3% | 78.4% | 74.7% | 73.9% | 74.6% | 73.3% |

## Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | | | |
|---|---|---|---|---|---|---|---|
| Cadden(1991) | General | NN/12 | *Year before failure* | *1* | *2* | *3* | |
| | | | ▪ Bankrupt firms | 90% | 90% | 80% | |
| | | | ▪ Non-bankrupt firms | 100% | 90% | 90% | |
| | | MDA/12 | ▪ Bankrupt firms | 80% | 60% | 60% | |
| | | | ▪ Non-bankrupt firms | 90% | 80% | 70% | |
| Espahbodi(1991) | *Banks* | Logit/4 | ▪ Bankrupt banks – 84% | | | | |
| | | | ▪ Non-bankrupt banks – 82% | | | | |
| | | | ▪ Bankrupt banks – 83% | | | | |
| | | MDA/4 | ▪ Non-bankrupt banks – 75% | | | | |
| Forsyth(1991) | *Quarterly models* | Logit/7 | Bankrupt firms – 71.9% to 93.8%, Non-bankrupt firms – 62.5% to 93.8% | | | | |
| George(1991) | General | Cox proportional hazards/7 | *Year before failure* | *1* | *2* | *5* | |
| | | | ▪ Bankrupt firms | 70% | 78% | 61% | |
| | | | ▪ Non-bankrupt firms | 90% | 92% | 95% | |
| Goudie and Meeks(1991) | *Macro & Micro perspectives; UK* | MDA/6 | Bankrupt firms – 67% to 87.2%, Non-bankrupt firms – 84% to 89.4% | | | | |
| Gregory-Allen and Henderson Jr. (1991) | General | Catastrophe/3 | All firms that filed for bankruptcy had at least one significant parameter shift (5% level) at some point in the 1,000 days prior to filing | | | | |
| Laitinen(1991) | *Small & mid-size Finnish firms* | MDA/6 | *Year before failure* | *1* | *2* | *4* | *6* |
| | | | ▪ Bankrupt firms | 90% | 72.5% | 57.5% | 65% |
| | | | ▪ Non-bankrupt firms | 87.5% | 65% | 52.5% | 60% |
| Luoma and Laitinen(1991) | *Finnish firms* | Proportional hazards/7 | *Model accuracy:* Bankrupt firms – 61.8%, Non-bankrupt firms – 61.8% | | | | |
| | | MDA/7 | Bankrupt firms – 64.7%, Non-bankrupt firms – 76.5% | | | | |
| | | Logit/7 | Bankrupt firms – 73.5%, Non-bankrupt firms – 70.6% | | | | |

## Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | | | |
|-------|-------------|-------------------|-------------------|---|---|---|---|---|---|
| Tam(1991) | *Banks* | MDA/9 | Failed banks – 59% to 75%, Non-failed banks – 60% to 95% | | | | | | |
| | | Logit/9 | | | | | | | |
| | | Nearest neighbor | Failed banks – 64% to 70%, Non-failed banks – 91% to 100% | | | | | | |
| | | Inductive | Failed banks – 59% to 80%, Non-failed banks – 75% to 95% | | | | | | |
| | | Dichotomizer 3 (ID3) | Failed banks – 60% to 77%, Non-failed banks – 82% to 95% | | | | | | |
| | | NN/9 | Failed banks – 68% to 98%, Non-failed banks – 80% to 95% | | | | | | |
| Theodossiou(1991) | *Greek manufacturing firms* | Linear Prob /8 | Bankrupt firms – 96.4%, Non-bankrupt firms – 77.8% | | | | | | |
| | | Logit/8 | Bankrupt firms – 95.5%, Non-bankrupt firms – 92.6% | | | | | | |
| | | Probit/8 | Bankrupt firms – 95.5%, Non-bankrupt firms – 92.6% | | | | | | |
| Baldwin and Glezen(1992) | *Quarterly models* | LDA/24 | *Quarter before failure* | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| | | | ▪ Bankrupt firms | 61% | 62% | 57% | 78% | 84% | 86% | 73% |
| | | | ▪ Non-bankrupt firms | 87% | 85% | 84% | 85% | 90% | 93% | 80% |
| Coats and Fant (1992) | General | NN/5 | Distressed firms – 91%%, Healthy firms – 96% | | | | | | |
| | | MDA/5 | Distressed firms – 72%, Healthy firms – 89% | | | | | | |
| Dwyer(1992) | General | Backpropagation neural network/9 | *Year before failure* | 1 | | 3 | | 5 | |
| | | | ▪ Bankrupt firms | 89% | | 73% | | 57% | |
| | | | ▪ Non-bankrupt firms | 69% | | 57% | | 64% | |
| | | Counter-propagation neural network/9 | ▪ Bankrupt firms | 95% | | 68% | | 76% | |
| | | Logit analysis (9 factors) | ▪ Non-bankrupt firms | 28% | | 45% | | 49% | |
| | | | ▪ Bankrupt firms | 90% | | 97% | | 80% | |
| | | Nonparametric DA/6 | ▪ Non-bankrupt firms | 62% | | 17% | | 43% | |
| | | | ▪ Bankrupt firms | 76% | | 70% | | 55% | |
| | | | ▪ Non-bankrupt firms | 57% | | 54% | | 57% | |
| Koundinya and Puri(1992) [Source: Clark, Foster, Hogan and Webster 1997] | General | Judgmental/9 | *Year before failure* | 1 | 2 | 3 | 4 | 5 | |
| | | | ▪ Failed firms | 71% | 100% | 86% | 86% | 100% | |
| | | | ▪ Ongoing firms | 100% | 100% | 100% | 100% | 100% | |
| Salchenberger, Cinar and Lash(1992) | *Savings & loan associations* | NN/5 | Failed S&Ls – 85.3%, Non-failed S&Ls – 99.4% | | | | | | |
| | | | Failed S&Ls – 72.0%, Non-failed S&Ls – 99.4% | | | | | | |

# Appendix A (continued)

## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | |
|---|---|---|---|---|---|
| Tam and Kiang(1992) | *Banks* | (19 factors) | *Year before failure* | *1* | *2* |
| | | MVA | ▪ Failed banks | 82% | 70% |
| | | | ▪ Non-failed banks | 86% | 95% |
| | | Logit | ▪ Failed banks | 68% | 85% |
| | | | ▪ Non-failed banks | 95% | 100% |
| | | k Nearest | ▪ Failed banks – 59% to 80% | | |
| | | neighbor | ▪ Non-failed banks – 75% to 95% | | |
| | | | ▪ Failed banks | 77% | 60% |
| | | Inductive Dichotomizer 3 (ID3) | ▪ Non-failed banks | 82% | 95% |
| | | | ▪ Failed banks – 68% to 98% | | |
| | | Neural network | ▪ Non-failed banks – 80% to 95% | | |
| Agarwal(1993) | General | NN with Nworks/5 | *Model accuracy for* hold-out sample: Failing companies – 40% to 68%, Healthy companies – 67% to 97% | | |
| | | Neural network with Pascal backpropagation algorithm/5 | Failing companies – 46% to 73%, Healthy companies – 71.5% to 94% | | |
| | | LDA/5 | | | |
| | | Logit/5 | Failing companies – 30.5% to 66.5%, Healthy companies – 70.5% to 91% | | |
| | | | Failing companies – 40% to 80%, Healthy companies – 56.5% to 86.5% | | |
| Arkaradejdachachai(1993) | *Manufacturing firms* | Logit/4 | Bankrupt firms – 69%, Non-bankrupt firms – 77% | | |
| Bukovinsky (1993) | General | MDA/11 | Model 1 (11 of 11 factors) – 87.39%, Model 2 (2 of 11 factors) – 89.19% | | |
| | | Logit/11 | ▪ Model 1 (11 of 11 factors) – 88.29% ▪ Model 2 (2 of 11 factors) – 90.09%* * Binomial tests of proportions on Logit Model 2 (the preferred model) showed that the cash-flow based model <u>cannot</u> distinguish between bankrupt and non-bankrupt firms. | | |

## Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | | |
|---|---|---|---|---|---|---|---|
| Fletcher and Goss (1993) | General | Logit/3 | Logit model – 71.3% | | | | |
| | | NN/3 | *Hidden layers of nodes* | *3* | *4* | *5* | *6* | *7* |
| | | | Model accuracy | 80.5% | 82.4% | 75.0% | 74.1% | 75.0% |
| Guan (1993) | General | NN/5 | *Network model* | *0* | *1* | *2* | *3* | *4* |
| | | | ▪ Bankrupt firms | 83% | 96% | 100% | 100% | 100% |
| | | | ▪ Non-bankrupt firms | 97% | 70% | 83% | 87% | 93% |
| | | MDA/5 | ▪ Bankrupt firms – 87% | | | | |
| | | | ▪ Non-bankrupt firms – 90% | | | | |
| | | MDA/4 | ▪ Bankrupt firms – 90% | | | | |
| | | | ▪ Non-bankrupt firms – 93% | | | | |
| Jiang (1993) | General | Non-parametric DA kernel method/5 | *Year before failure* | *1* | *2* | *3* | *4* | *5* |
| | | | *Model accuracy (unequal smoothing parameters) for* hold-out samples: | | | | |
| | | | ▪ Bankrupt firms | 91% | 88% | 85% | 71% | 69% |
| | | | ▪ Non-bankrupt firms | 97% | 86% | 75% | 76% | 72% |
| | | Logit/5 | ▪ Bankrupt firms | 76% | 78% | 84% | 75% | 77% |
| | | | ▪ Non-bankrupt firms | 82% | 71% | 74% | 68% | 69% |
| Odom and Sharda(1993) | General | NN/5 | Bankrupt firms – 81.48%, Non-bankrupt firms – 82.14% | | | | |
| | | MDA/5 | Bankrupt firms – 59.26%, Non-bankrupt firms – 89.29% | | | | |
| Raghupathi, Schkade and Raju(1993) | General | Neural network (14 factors) | *Number of nodes* | *10_0* | *15_0* | *20_0* | *10_2* | *10_4* | *15_2* |
| | | | Model accuracy (approximate) | 66% | 76% | 71% | 73% | 75% | 86% |
| Rahimian, Singh, Virmani & Thammachote (1993) | General | NN/5 Backpropagation | Bankrupt firms – 77.8%, Non-bankrupt firms – 85.7% | | | | |
| | | Athena (entropy measure) | ▪ Bankrupt firms – 77.8% | | | | |
| | | | ▪ Non-bankrupt firms – 85.7% | | | | |
| | | Perceptron (no hidden layer) | ▪ Bankrupt firms – 77.8% | | | | |
| | | | ▪ Non-bankrupt firms – 85.7% | | | | |
| Theodossiou(1993) | General Note: Model accuracy based on 2 failed firms and 2 non-failed firms. | Multivariate cumulative sum (CUSUM)/5 | *Model accuracy for* hold-out sample: | | | | |
| | | | ▪ Failed firms – 100% | | | | |
| | | | ▪ Non-failed firms – 100% | | | | |

## Appendix A (continued0
## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] |
|---|---|---|---|
| Wertheim and Lynn(1993) | *Hospitals* | Logit/6 | *Model accuracy:*<br>• Bankrupt firms – 64.7% to 78.3%<br>• Non-bankrupt firms – 63.3% to 76.1% |
| Hopwood, McKeown and Mutchler(1994) | General | Logit/7<br><br>Note: One variable differs from 1989 | *Model accuracy (with stress partition, misclassification costs ratio 100:1):*<br>• Non-bankrupt stressed firms – 66.7%<br>• Bankrupt stressed firms – 81.1%<br>• Non-stressed firms – 100% |
| Johnsen and Melicher(1994) | General | (12 factors)<br>Binomial logit analysis<br><br>Multinomial logit analysis | *Model accuracy:*<br>• Bankrupt firms – 76.79% to 77.68%<br>• Non-bankrupt firms – 94.88% to 95.56%<br><br>• Bankrupt firms – 90.18% to 94.64%<br>• Non-bankrupt firms – 98.29% |
| Nittayagasetwat(1994) | General | NN/10<br><br>Logit/10<br><br>Recursive partitioning/10 | Model accuracy for *hold-out sample* – 83.25%<br><br>Model accuracy for *hold-out sample* – 75.74%<br><br>Model accuracy for *hold-out sample* – 73.12% |
| Nour(1994) | General | NN/5<br>Kohonen self-organizing algorithm (KSO)<br><br>Modified algorithm MCM-1<br><br>Modified algorithm MCM-2 | • Bankrupt firms – 88.15%<br>• Non-bankrupt firms – 56.43%<br><br>• Bankrupt firms – 88.67%<br>• Non-bankrupt firms – 63.21%<br><br>• Bankrupt firms – 92.96%<br>• Non-bankrupt firms – 62.14% |

Appendix A (continued)
Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] |
|---|---|---|---|
| Platt, Platt and Pedersen (1994) | *Oil & gas companies* | Logit/6 | • Bankrupt firms – 80% to 94%<br>• Non-bankrupt firms – 91% to 96% |
| Tsukuda and Baba(1994) | *Japanese manufacturing firms* | NN/21 | *Model accuracy for* hold-out sample: Listed firms (11 of 21 factors)<br>Bankrupt firms – 83 to 100%, Non-bankrupt firms – 60 to 100%% |
| Ward(1994) | General | LogiT/9 | *Year before failure*        1    2    3<br>*Ranked probability score for* hold-out sample:<br>• Financially healthy firms (111 possible)   107.6   105.8   105.0<br>• Firms reducing cash dividend payments (17 possible)   13.5   13.7   13.7<br>• Firms with loan default/debt accommodation (14 possible) 11.3   10.4   9.7<br>• Bankrupt firms (16 possible)   8.3   10.0   5.6 |
| Wilson and Sharda(1994) | General | NN/5 | Bankrupt firms – 47% to 97%, Non-bankrupt firms – 96% to 99% |
| Boritz and Kennedy(1995) | General | (14 factors) Backpropagation (NN)<br><br>Optimal estimation NN<br><br>LDA<br><br>Quadratic DA<br><br>Non-param DA<br><br>Logit analysis<br><br>Probit analysis | Bankrupt firms – 74.27%,Non-bankrupt firms – 84.03%<br><br><br>Bankrupt firms – 71.41%, Non-bankrupt firms – 26.65%<br><br><br>Bankrupt firms – 72.51%, Non-bankrupt firm – 87.34%<br><br>Bankrupt firms – 67.32%, Non-bankrupt firms – 75.40%<br>Bankrupt firms – 74.10%, Non-bankrupt firms – 86.87%<br><br>Bankrupt firms – 75.26%, Non-bankrupt firms – 83.90%<br><br>Bankrupt firms – 74.90%, Non-bankrupt firms – 83.90% |
| El-Temtamy(1995) | *U.S. oil & gas companies* | NN/11<br><br>Logit/11 | Bankrupt firms – 71.43% to 100%, Non-bankrupt firms – 91.51% to 100%<br><br>Bankrupt firms – 69.64% to 94.64%, Non-bankrupt firms – 68.87% to 96.23% |
| Martin-del-Brio and Serrano-Cinca(1995) | *Spanish banks* | NN/9 | Found good predictors of bankruptcy to be: Net income / Assets, Net income / Equity capital, Net income / Loans, Cost of sales / Sales, Cash flow / Loans |
| Martin-del-Brio and Serrano-Cinca(1995) | *Spanish firms* | NN5 | Weight map allows one to distinguish companies into distinct regions and trace companies' evolutions |

# Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | | |
|---|---|---|---|---|---|---|
| McKee(1995) | General | Interactive Dichotomizer 3 (ID3)/8 | *Model accuracy for* hold-out sample – 75% to 97.5% | | | |
| Poddig(1995) | *French firms* | Backpropogation NN/12 | *Year before failure* | *1* | *2* | *3* |
| | | | Model accuracy for *hold-out sample* | 89-93% | 83-89% | 82-86% |
| | | Learning vector quantiser/5 | Model accuracy *hold-out sample* | 70% | 74% | 84% |
| | | | Note: Factors not disclosed. | | | |
| ‡Rudorfer(1995) | *Private limited Austrian firms* | Neural network (5 factors) | Model accuracy for failed firms (best: 5-3-1 and 5-5-1 networks) – 96% | | | |
| Rujoub, Cook and Hay (1995) | General | MDA/14 | ▪ Bankrupt firms – 45% to 82% <br> ▪ Non-bankrupt firms – 52% 5o 100% | | | |
| Wilson, Chong and Peel (1995) | *UK firms* | NN/18 | ▪ Failed firms – 70% to 95% <br> ▪ Non-failed firms – 82.5% to 95% <br> ▪ Distressed acquired firms – 50% | | | |
| Alici(1996) | *UK manufacturing firms* | NN/28 | Failed firms – 71.38%, Non-failed firms – 76.07% | | | |
| | | NN/9 | Failed firms – 67.52%, Non-failed firms – 71.43% | | | |
| | | MDA/4 | Failed firms – 60.12%, Non-failed firms – 71.07% | | | |
| | | Logit/4 | Failed firms – 65.27%, Non-failed firms – 66.79% | | | |
| Bryant(1996) | General | Case-based reasoning – artificial intelligence system/25 | *Year before failure* | *1* | *2* | *3* |
| | | | *Model accuracy (1975-1989 data):* | | | |
| | | | ▪ Bankrupt firms | 27.3% | 17.1% | 9.7% |
| | | | ▪ Non-bankrupt firms | 95.2% | 97.6% | 94.8% |
| | | | *Model accuracy (1990-1994 data):* | | | |
| | | | ▪ Bankrupt firms | 27.1% | 10.7% | 10.0% |
| | | | ▪ Non-bankrupt firms | 95.1% | 97.1% | 95.4% |
| Gardiner, Oswald and Jahera (1996) | *Hospitals* | Multivariate discriminant analysis (12 factors) | *Model predictions for* hold-out samples: <br> ▪ Failed hospitals misclassified – 4% to 32% <br>   Percent unclassified – 4% to 11% <br> ▪ Non-failed hospitals misclassified – 14% to 19% <br>   Percent unclassified – 1% to 9% | | | |

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | |
|---|---|---|---|---|---|
| Henebry(1996) | *Banks* | Proportional hazards/26 | Bankrupt firms – 93.55% to 99.55%, Non-bankrupt firms – 1.5% to 57.81% | | |
| Lee, Han and Kwon(1996) | *Korean firms* | (29 factors) Inductive Dichotomizer 3 | Model accuracy – 68% to 70% Model accuracy – 72.86% to 77.5% | | |
| | | *Hybrid NN:* MDA-assisted | Model accuracy – 70% to 80% | | |
| | | ID3-assisted | Model accuracy – 73% to 82.5% | | |
| | | Self-organizing feature map MDA-assisted | Model accuracy – 74.3% to 82.5% | | |
| | | SOFM ID3-assisted | Model accuracy – 74% to 80% | | |
| Leshno and Spector (1996) | General | Nn/41 | *Year before failure* | *1* | *2* |
| | | | ▪ Bankrupt firms | 56.7% to 71.4% | 59.3% to 75.2% |
| | | | ▪ Non-bankrupt firms | 73.5% to 82.2% | 74.5% to 79.5% |
| Lindsay and Campbell (1996) | General | Chaos theory/1 | Bankrupt firms – 65%, Non-bankrupt firms – 65% | | |
| | | MDA/2 | Bankrupt firms – 71%, Non-bankrupt firms – 80% | | |
| | | Combined model (3 factors) | ▪ Bankrupt firms – 80% ▪ Non-bankrupt firms – 88% | | |
| McGurr(1996) | *Retail firms* | MDA/7 | Model accuracy – 69.7% to 75.26% on various validation samples | | |
| Serrano-Cinca(1996) | General | NN/5 | Model accuracy for *hold-out sample* – 83.6% | | |
| Jo, Han and Lee(1997) | *Korean firms* | MDA/57 | Model accuracy – 81.97% to 82.43% | | |
| | | NN/57 | Model accuracy – 82.01% to 86.36% | | |
| | | Case-based forecasting /57 | Model accuracy – 80.81% to 81.88% | | |

# Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model[6]/Factors | Model Accuracy[4] | | | | |
|---|---|---|---|---|---|---|---|
| Kiviluoto(1998) | Small & medium-size Finnish firms | Learning vector quantization/4 | Bankrupt firms – 34.8%, Non-bankrupt firms – 97.3% | | | | |
| | | NN/4 | Bankrupt firms – 24.8%, Non-bankrupt firms – 98.5% | | | | |
| | | LDA/4 | Bankrupt firms – 52.9%, Non-bankrupt firms – 93.4% | | | | |
| | | QDA/4 | Bankrupt firms – 44.1%, Non-bankrupt firms – 93.5% | | | | |
| Zordan(1998) | Retail/Wholesale & Manufacturing firms | MDA/30 | • Failed firms – 78.7% to 85.2% <br> • Non-failed firms – 66.7% to 68.5% | | | | |
| Dimitras, Slowinski, Susmaga and Zopounidis (1999) | Greek firms | Rough set theory (12 factors) | *Year before failure* | 1 | 2 | 3 | |
| | | | • Bankrupt firms | 73.7% | 47.4% | 36.8% | |
| | | | • Non-bankrupt firms | 57.9% | 68.4% | 68.4% | |
| | | MDA/12 | • Bankrupt firms | 63.2% | 42.1% | 36.8% | |
| | | | • Non-bankrupt firms | 68.4% | 63.7% | 73.7% | |
| | | Logit/12 | • Bankrupt firms | 63.2% | 31.6% | 36.8% | |
| | | | • Non-bankrupt firms | 57.9% | 84.2% | 84.2% | |
| Gao(1999) | Hospitality (lodging & restaurant) firms | MDA/5 | *Model accuracy:* <br> • Bankrupt firms – 52% to 88% <br> • Non-bankrupt firms – 96% to 100% | | | | |
| Kahya and Theodossiou (1999) | General | Time-series Cum Sums (CUSUM) (4 factors) | *Period before failure* | 1 | 2 | 3 | 4 |
| | | | • Failed firms | 82% | 60% | 54% | 39% |
| | | | • Healthy firms | 83% | N/A | N/A | N/A |
| | | MDA/4 | • Failed firms | 69% | 53% | 44% | 18% |
| | | | • Healthy firms | 87% | N/A | N/A | N/A |
| | | Logit/4 | • Failed firms | 68% | 49% | 43% | 30% |
| | | | • Healthy firms | 84% | N/A | N/A | N/A |
| Lennox(1999) | UK firms | Probit analysis (9 factors) | *Period before failure* | 1 | 2 | | |
| | | | • Bankrupt firms | 48.48% | 38.10% | | |
| | | | • Non-bankrupt firms | 97.85% | 97.84% | | |

Appendix A (continued)
## Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | |
|---|---|---|---|---|---|
| Sung, Chang and Lee(1999) | *Korean mfg. firms* | | *Economic conditions of model* | *Normal* | *Crisis* |
| | | | ▪ Bankrupt firms | 72.4% | 66.7% |
| | | NN/5 | ▪ Non-bankrupt firms | 90.0% | 88.9% |
| | | | ▪ Bankrupt firms | 69.0% | 53.3% |
| | | MDA/5 | ▪ Non-bankrupt firms | 89.8% | 85.2% |
| Yang, Platt and Platt(1999) | *Oil & gas companies* | NN:Back-propagation/5 | Bankrupt firms – 0% to 50%, Non-bankrupt firms – 80% to 100% | | |
| | | Probabilistic NN | Bankrupt firms – 13% to 25%, Non-bankrupt firms – 80% | | |
| | | Probabilistic NN without patterns normalized/5 | Bankrupt firms – 50% to 63%, Non-bankrupt firms – 80% to 90% | | |
| | | MDA/5 | Bankrupt firms – 88%, Non-bankrupt firms – 67% to 87% | | |
| Zhang, Hu, Patuwo and Indro(1999) | *Manufacturing firms* | NN/6 | Bankrupt firms – 85 to 93%, Non-bankrupt firms – 83 to 87% | | |
| | | Logit/6 | Bankrupt firms – 74 to 79%,Non-bankrupt firms – 78 to 81% | | |
| Zopounidis and Doumpos (1999) | *Greek firms* | Utilities Additives DIScriminantes (UTADIS)/12 | Bankrupt firms – 47.37% to 84.21%, Non-bankrupt firms – 52.63% to 78.95% | | |
| Alam, Booth, Lee and Thordarson(2000) | *Banks* | (NN/5) Self-organizing | Misclassified 2 problem banks; remaining problem, failed, and healthy banks identified into seemingly appropriate clusters | | |
| | | Competitive | Misclassified 2 problem banks; remaining problem, failed, and healthy banks identified into seemingly appropriate clusters | | |
| | *Computer and peripheral mfg,, software & merch* | NN/8 | Bankrupt firms – 83%, Non-bankrupt firms – 72% | | |

Appendix A (continued)

Models for Assessing Bankruptcy

| Study | Application[3] | Model [6]/Factors | Model Accuracy[4] | | |
|---|---|---|---|---|---|
| Lee (2001) | *Korean firms* | (NN/5) Backpropagation | *Year before failure* | 2 | 3 |
| | | | • Matched firms | 73.81% | 69.05% |
| | | | • Unmatched firms – 84.56% | | |
| | | Kohonen self-organizing | • Matched firms | 66.67% | 76.19% |
| | | | • Unmatched firms – N/A | | |
| | | | • Matched firms | 57.14% | 61.90% |
| | | Logit analysis | • Unmatched firms – 52.94% | | |
| | | | • Matched firms | 59.52% | 61.90% |
| | | MDA | • Unmatched firms – 52.21% | | |
| Patterson(2001) | *Casinos* | MDA/12 | Failed firms – 100%, Non-failed firms – 89% | | |
| Shumway(2001) | General | Hazard13 | *Model accuracy for* hold-out sample – 0.9% to 75% | | |
| Gaeremynck, Willekens (2003) | *Belgian private* | Logit/8 | Model accuracy – 72.4%% | | |
| Grover(2003) | *Manufacturing firm* | MDA/6 | Model accuracy for *hold-out sample* – 78.17% | | |
| Anandarajan, Lee and Anandarajan(2004) | General | NN Genetic algorithm/5 Backpropagation NN | *Model accuracy for* hold-out sample:<br>Bankrupt firms – 95.5%, Non-bankrupt firms – 93.8%<br>Bankrupt firms – 93.8%, Non-bankrupt firms – 70.0% | | |
| | | MDA | Bankrupt firms – 82.8%, Non-bankrupt firms – 21.7% | | |
| Jones and Hensher(2004) | *Includes financial services firms* | Mixed logit analysis/7 | Bankrupt firms – Predicted 2.02% to 2.37% compared to actual 1.84% to 2.17%<br>Non-bankrupt firms – Predicted 95.8% to 96.2% compared to actual 95.6% to 96.2% | | |
| | | Multinomial logit analysis/7 | Bankrupt firms – Predicted 0.02% to 0.13% compared to actual 1.84% to 2.15%<br>Non-bankrupt firms – Predicted 99.27% to 99.38% compared to actual 95.5% to 96.2% | | |
| Wang(2004) | *Internet firms* | Logit/8 | Bankrupt firms – 26.7%, Non-bankrupt firms – 90.8% | | |

## Appendix B
## Factors Included in Five or More Studies[5]

| Factor/Consideration | Number of Studies that Include |
|---|---|
| Net income / Total assets | 54 |
| Current ratio | 51 |
| Working capital / Total assets | 45 |
| Retained earnings / Total assets | 42 |
| Earnings before interest and taxes / Total assets | 35 |
| Sales / Total assets | 32 |
| Quick ratio | 30 |
| Total debt / Total assets | 27 |
| Current assets / Total assets | 26 |
| Net income / Net worth | 23 |
| Total liabilities / Total assets | 19 |
| Cash / Total assets | 18 |
| Market value of equity / Book value of total debt | 16 |
| Cash flow from operations / Total assets | 15 |
| Cash flow from operations / Total liabilities | 14 |
| Current liabilities / Total assets | 13 |
| Cash flow from operations / Total debt | 12 |
| Quick assets / Total assets | 11 |
| Current assets / Sales | 10 |
| Earnings before interest and taxes / Interest | 10 |
| Inventory / Sales | 10 |
| Operating income / Total assets | 10 |
| Cash flow from operations / Sales | 9 |
| Net income / Sales | 9 |
| Long-term debt / Total assets | 8 |
| Net worth / Total assets | 8 |
| Total debt / Net worth | 8 |
| Total liabilities / Net worth | 8 |
| Cash / Current liabilities | 7 |
| Cash flow from operations / Current liabilities | 7 |
| Working capital / Sales | 7 |
| Capital / Assets | 6 |
| Net sales / Total assets | 6 |
| Net worth / Total liabilities | 6 |
| No-credit interval | 6 |
| Total assets (log) | 6 |
| Cash flow (using net income) / Debt | 5 |
| Cash flow from operations | 5 |
| Operating expenses / Operating income | 5 |
| Quick assets / Sales | 5 |
| Sales / Inventory | 5 |
| Working capital / Net worth | 5 |