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A Review of Bankruptcy Prediction Studies: 1930-Present

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A Review of Bankruptcy Prediction Studies: 1930 to 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.

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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% ▪ 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* — *2* / *3* / *4* Model accuracy — 89.0% / 84.3% / 78.1%
Earl and Marais(1979) [Source: Taffler 1984]	*UK manufacturing & distribution firms*	MDA/4	*Year before failure* — *1* / *2* ▪ Failing firms — 97% / 92% ▪ Non-failing firms — 91% / 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* — *1* / *2* / *1 or 2* / *1** Model accuracy — 96% / 96% / 93% / 96.3% * With 2 additional factors: Cash flow from operations / Sales; Intangibles + deferred assets / Total assets
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% Cash flow / Total debt most significant univariate discriminator
Sharma and Mahajan(1980)	*Retail firms*	MDA/2	*Year before failure* — *1* / *2* / *3* / *4* / *5* Model accuracy — 92% / 78% / 74% / 73% / 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% Bankrupt Firms SPL model outperforms HC model at probability of non-failure cutoff .41-.875 HC model outperforms SPL model at probability of non-failure cutoff .125-41 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 fims.	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	*Year before failure* 1 3 *(means)* ▪ Weak firms 69.6% 78.2% ▪ Non-weak firms 73.9% 69.6%
		Probit/8	▪ 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*	*1*	*2*	*3*	*4*	*5*
			Model accuracy	88.8%	80.6%	72.5%	77.1%	80.9%
		Logit/6	Bankrupt firms	85.7%	85.7%	79.6%	81.3%	84.8%
			▪ Non-bankrupt firms	98.0%	83.7%	77.6%	79.2%	76.7%
Dambolena &Shulman,1988	General	Logit/14	Failed firms – 84% to 98%, Non-failed firms – 68% to 86%					
Gloubos and Grammatikos (1988) [Source: Altman 2002]	*Greek firms*	Linear probability model/5	*Year before failure*	*1*	*2*	*3*		
			▪ Bankrupt firms	70.8%	60.9%	64.3%		
			▪ Non-bankrupt firms	75.0%	82.6%	78.6%		
		Probit/5	▪ Bankrupt firms	70.8%	60.9%	42.9%		
			▪ Non-bankrupt firms	75.0%	82.6%	78.6%		
		Logit/5	▪ Bankrupt firms	66.7%	60.9%	50.0%		
			▪ Non-bankrupt firms	87.5%	82.6%	78.6%		
		MDA/5	▪ Bankrupt firms	66.7%	60.9%	64.3%		
			▪ Non-bankrupt firms	66.7%	82.6%	85.7%		
McNamara, Cocks and Hamilton(1988)	*Private Australian firms*	MDA/6	Bankrupt firms – 86.4%, Non-bankrupt firms – 83.3%					
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 *Turkish food sector firms*	Multivariate discriminant analysis (6 factors)	*Model accuracy:* ▪ 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 NN/11	Bankrupt firms – 69.5%, Non-bankrupt firms – 97.3% 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 neighbor	▪ Failed banks – 59% to 80% ▪ Non-failed banks – 75% to 95%		
		Inductive Dichotomizer 3 (ID3)	▪ Failed banks	77%	60%
			▪ Non-failed banks	82%	95%
		Neural network	▪ Failed banks – 68% to 98% ▪ 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 cannot 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:* ▪ Bankrupt firms – 64.7% to 78.3% ▪ Non-bankrupt firms – 63.3% to 76.1%
Hopwood, McKeown and Mutchler(1994)	General	Logit/7 Note: One variable differs from 1989	*Model accuracy (with stress partition, misclassification costs ratio 100:1):* ▪ Non-bankrupt stressed firms – 66.7% ▪ Bankrupt stressed firms – 81.1% ▪ Non-stressed firms – 100%
Johnsen and Melicher(1994)	General	(12 factors) Binomial logit analysis Multinomial logit analysis	*Model accuracy:* ▪ Bankrupt firms – 76.79% to 77.68% ▪ Non-bankrupt firms – 94.88% to 95.56% ▪ Bankrupt firms – 90.18% to 94.64% ▪ Non-bankrupt firms – 98.29%
Nittayagasetwat(1994)	General	NN/10 Logit/10 Recursive partitioning/10	Model accuracy for *hold-out sample* – 83.25% Model accuracy for *hold-out sample* – 75.74% Model accuracy for *hold-out sample* – 73.12%
Nour(1994)	General	NN/5 Kohonen self-organizing algorithm (KSO) Modified algorithm MCM-1 Modified algorithm MCM-2	▪ Bankrupt firms – 88.15% ▪ Non-bankrupt firms – 56.43% ▪ Bankrupt firms – 88.67% ▪ Non-bankrupt firms – 63.21% ▪ Bankrupt firms – 92.96% ▪ 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% ▪ Non-bankrupt firms – 91% to 96%
Tsukuda and Baba(1994)	*Japanese manufacturing firms*	NN/21	*Model accuracy for* hold-out sample: <u>Listed firms</u> (11 of 21 factors) Bankrupt firms – 83 to 100%, Non-bankrupt firms – 60 to 100%%
Ward(1994)	General	LogiT/9	*Year before failure* — *1* / *2* / *3* *Ranked probability score for* hold-out sample: ▪ Financially healthy firms (111 possible) — 107.6 / 105.8 / 105.0 ▪ Firms reducing cash dividend payments (17 possible) — 13.5 / 13.7 / 13.7 ▪ Firms with loan default/debt accommodation (14 possible) — 11.3 / 10.4 / 9.7 ▪ 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)	Bankrupt firms – 74.27%,Non-bankrupt firms – 84.03%
		Optimal estimation NN	Bankrupt firms – 71.41%, Non-bankrupt firms – 26.65%
		LDA	Bankrupt firms – 72.51%, Non-bankrupt firm – 87.34%
		Quadratic DA	Bankrupt firms – 67.32%, Non-bankrupt firms – 75.40%
		Non-param DA	Bankrupt firms – 74.10%, Non-bankrupt firms – 86.87%
		Logit analysis	Bankrupt firms – 75.26%, Non-bankrupt firms – 83.90%
		Probit analysis	Bankrupt firms – 74.90%, Non-bankrupt firms – 83.90%
El-Temtamy(1995)	*U.S. oil & gas companies*	NN/11	Bankrupt firms – 71.43% to 100%, Non-bankrupt firms – 91.51% to 100%
		Logit/11	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 Learning vector quantiser/5	*Year before failure* — *1*, *2*, *3* Model accuracy for *hold-out sample* — 89-93%, 83-89%, 82-86% 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% ▪ Non-bankrupt firms – 52% 5o 100%
Wilson, Chong and Peel (1995)	*UK firms*	NN/18	▪ Failed firms – 70% to 95% ▪ Non-failed firms – 82.5% to 95% ▪ Distressed acquired firms – 50%
Alici(1996)	*UK manufacturing firms*	NN/28 NN/9 MDA/4 Logit/4	Failed firms – 71.38%, Non-failed firms – 76.07% Failed firms – 67.52%, Non-failed firms – 71.43% Failed firms – 60.12%, Non-failed firms – 71.07% 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: ▪ Failed hospitals misclassified – 4% to 32% Percent unclassified – 4% to 11% ▪ Non-failed hospitals misclassified – 14% to 19% Percent unclassified – 1% to 9%

Appendix A (continued)
Models for Assessing Bankruptcy

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 *Hybrid NN:* MDA-assisted ID3-assisted Self-organizing feature map MDA-assisted SOFM ID3-assisted	Model accuracy – 68% to 70% Model accuracy – 72.86% to 77.5% Model accuracy – 70% to 80% Model accuracy – 73% to 82.5% Model accuracy – 74.3% to 82.5% 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 MDA/2 Combined model (3 factors)	Bankrupt firms – 65%, Non-bankrupt firms – 65% Bankrupt firms – 71%, Non-bankrupt firms – 80% ▪ 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 NN/57 Case-based forecasting /57	Model accuracy – 81.97% to 82.43% Model accuracy – 82.01% to 86.36% 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% ▪ 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:* ▪ Bankrupt firms – 52% to 88% ▪ 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	*Korean firms*	(NN/5)	*Year before failure*	*2*	*3*
(2001)		Backpropagation	▪ Matched firms	73.81%	69.05%
			▪ Unmatched firms – 84.56%		
		Kohonen self-organizing	▪ Matched firms	66.67%	76.19%
			▪ Unmatched firms – N/A		
		Logit analysis	▪ Matched firms	57.14%	61.90%
			▪ Unmatched firms – 52.94%		
		MDA	▪ Matched firms	59.52%	61.90%
			▪ 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	*Model accuracy for* hold-out sample: Bankrupt firms – 95.5%, Non-bankrupt firms – 93.8%		
		Backpropagation NN	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% 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% 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