A Quest for a Signal Forecasting Corporate Failure: The 'KPP' Model for Bankruptcy Prediction

Dev Prasad
University of Massachusetts Lowell

Yash R. Puri
University of Massachusetts Lowell

Rama Koundinya
University of Massachusetts Boston

Financial distress leading to corporate or institutional failure result in significant losses of economic value, employment, personal income, and tax revenues. For almost a century, researchers have studied the problems and have proposed alternate models for bankruptcy prediction - traditional as well as non-traditional such as the use of neural networks. The motivation for the utilization of bankruptcy prediction models could be self- improvement, regulatory purposes, investment purposes, and so on. However, smaller business organizations and individual investors are not likely to have the resources and technology to utilize the more complex models. An analysis utilizing the KPP model presented in this study shows that the credit risk profiles generated by this model are excellent predictors of financial distress and bankruptcy risk. The KPP model also acts as an early warning signal since bankruptcy could be predicted as far back as five years before the date of bankruptcy.

Keywords: Altman Z-score, analytical hierarchy, credit quality, expertise, financial distress, KPPZ-score, judgement, risk scoring

INTRODUCTION

For more than a century, business organizations and financial institutions have formed the backbone of the economy and been a source of livelihood and wealth for individuals. The Great Depression of 1929 showed that wealth could be a fickle mistress. Jobs and money are not guaranteed for all life. The economy has gone through several cycles of expansion and recession. Volatile interest rates, large debt burdens, increasingly deeper and longer recessionary cycles, and intense competition had put to test even the well-managed firms in traditionally strong industries. For example, the surge in the economy in the early and mid-1990s was again followed by a collapse which led to a very large number of bankruptcy filings in the late 1990s into 2001 and continuing into 2020. Corporate bankruptcy had costly economic implications for the macro economy and the immediate stakeholders. Significant resource misallocation caused by firm failure placed a heavy burden on the economy as is evident from an article in the Boston Globe of December

28, 2003, which suggests that state treasurers are '…waging a campaign to clean up Wall Street' because they have been '…burned from losing billions of dollars in scandals and bankruptcies.' Further, according to the same article, the crash of Worldcom in 2002 '…cost California's two biggest funds $850 million.' Losses of portfolio values, employment, income, and tax revenues must be absorbed in every bankruptcy. For example, another Boston Globe article (January 6, 2004), states that the 2001 bankruptcy of Enron '…left creditors owed a record $67 billion…at least 5,600 Enron workers lost jobs…company auditor Arthur Andersen LLP didn't survive the accounting scandal…wiped out $68 billion of shareholder value.' Despite all these lessons, another great recession started in late 2007 continuing into mid-2009 which started with a meltdown of financial institutions. For the investor, the loss in wealth was about 54% on an average but in some cases, such as Ford Motors, the loss was even higher at about 90%. Though the economy has recovered mainly due to the billions of dollars of bail-out money poured in by the governments around the world, slashing of interest rates etc. etc., the threat of bankruptcy still looms over many. Household names such as Borders, Circuit City, Radio Shack, Toys R Us, Filenes and so many more have disappeared. Additional factors such as globalization, online competition etc. have crept in. Companies such as Macys, JC Penney, Sears etc. are closing stores and taking other steps to keep their business viable. Clearly, any approach that can improve insights into the evolution of financial distress and provide early warning signals of impending failure is likely to be of great value to all stakeholders and economic policy makers. The extensive volume of research devoted to corporate bankruptcy prediction speaks to the continuing need of understanding the bankruptcy phenomenon and improving the forecasting of corporate failure.

Traditional approaches to studies on firm failure and bankruptcy prediction explored the behavior of financial ratio measures and used multivariate statistical techniques to build prediction models. The information contents of the financial variables were assessed using paired sampling techniques. A number of these models performed well. However, the lack of precision in these variables, and the failure to incorporate the role of management are difficulties inherent in a purely empirical approach to the analysis of firm failure and supports the case for new approaches. Perceptions of risk by the management varies among firms, and their ability to deal with it in a timely fashion can make the difference between eventual failure, and near failure. In addition, management intervention materially affects the financial measures of failing firms in ways distinct from those of ongoing firms. Methodologies that enable incorporation of expert assessment of financial information would lead to an improved understanding of the evolution of bankruptcy risk. Nwogugu [2003] discusses the inter-relationship between sociological, behavioral, government policy, legal issues, and corporations some of which may become financially distressed.

This study details the KPP model itself but continues the examination of the efficacy of the KPP model across industries beyond the studies of Prasad et al (2010) as well as Prasad and Puri (2005). As detailed below, the KPP model combines expertise and judgement to the prediction of corporate failure through the application of an analytic hierarchy process to assess the risk profiles of firm failure. These assessed risk profiles are then evaluated as predictors of the onset of bankruptcy risk.

The study is organized in to seven sections. The first section is a review of prior studies. The analytic hierarchy process methodology is outlined in the second section. In the third section the hierarchy model for credit quality risk scoring is presented. Section four discusses the credit quality scoring scheme based on the hierarchy model. In the fifth section computation of credit quality score profiles for bankrupt, and a reference group of ongoing firms in selected industries is discussed. Profiles of failing firms are analyzed in the sixth section to further assess the efficiency of the model scores as useful indicators of firm failure. The last section presents concluding comments.

BACKGROUND

Studies on corporate bankruptcy and the related behavior of financial variables dates to the 1930's. Ramser and Foster [1931], Fitzpatrick [1932], and Winakor and Smith [1935] laid the groundwork for paired sampling approach to the understanding of the relative behavior of financial ratios of failed and non-failed firms. A number of these early studies are reviewed by Lev [1974]. Beaver's [1966] study, a classic among these early studies, is the culmination of univariate analysis of behavior of failing firm's financial ratios and a precursor to the development of multivariate analysis.

Altman [1968] in his first study using multivariate methods analyzed the discriminating power of a selected set of financial variables. This study was followed by a number of researchers in the sixties and seventies, and are extensively reviewed by Altman et al. [1981], Scott [1981], Altman [1971], Dambolina [1983], and Zavgren [1983]. A number of these studies are extensions of the discriminant analysis methodology to different sets of firms in a variety of industries. (See for example Edminster [1972], Santomero and Vinso [1977], White and Turnbull [1975]). Another group of studies attempted to improve upon the discriminant analysis models with refinements on the variable sets, including the impact of inflation (Norton and Smith [1979]) and the stability of ratios (Dambolina and Khoury [1980]). A third group approached the problem of prediction using alternate statistical methodologies. Wilcox's [1971] gambler's ruin model, Ohlsons's [1980], and Zevgren's [1983] logit models are examples of alternative statistical approaches. A survey by Jones [1987] provides an excellent review of a number of techniques used in studies on bankruptcy prediction up to the mid-1980s. Some recent extensions relate to improving the predictive accuracy involve the use of variables such as cash flow (Henebry [1996]) and market data (Curry et al [2002]) in the case of banks. Some other extensions relate to application of the models to the firms of other countries (for example: Nam and Jinn [2000], Altman et al [1995]). Also, some extensions have related to the methodology for prediction. For example, Pinado and Rodrigues [2001] develop a parsimonious model for small companies. Theodossiou and Kahya [1999] develop a time-series cumulative sums (CUSUM) model which they find to be robust over time and which performs better than models based on Linear Discriminant Analysis and Logit. Almost all the studies related to firm prediction rely on statistical procedures to develop models for prediction of financial distress. Further, Begley et al [1997] examine both the 1968 Altman model and 1980 Ohlson model and show that predictability performance of these models vary when applied over different time periods. Clark et al [1997] find favorable results of the expert system approach versus the traditional approach. On a cautionary note, Leclere [2002] suggests the influence of the choice of time dependence on model estimation. Yet another alternate approach using neural networks to model and predict financial distress was presented by Abid and Zouari [2003].

With the advent of faster and faster computers with greater and greater computing capacity, the analysis of larger sets became possible and allowed the use of more complex models. During the late 1990s and onwards several such models were developed and presented such as those by F Barboza, H Kimura, E Altman [2017], TE McKee [2003], H Ahn, K Kim [2009], JH Min, C Jeong [2009], C Charalambous, A Charitou, F Kaourou [2000], SH Min, J Lee, I Han [2006], Q Yu, Y Miche, E Séverin, A Lendasse [2014] and others. There are variations in the complexity of the methodology which in turn results in variations in the level of accuracy of predictions specially across time. Usually governments, financial institutions, large business organizations, large institutional investors and the like are likely to have the resources and technology to utilize some, if not all, of these models.

However, the same is not generally true for small and medium business organizations or for individual investors. Simpler models with early warning signals would meet their needs better. The continuing popularity of the Altman Z (as detailed in Altman [2018]) model cannot be disputed despite its accuracy being highest in the year prior to actual bankruptcy and then decreases in previous years. The above discussion suggests that further research is required in the financial distress area including the development of new techniques specially if they can improve the earliness of warning signals. Encouraged by the favorable results of the Prasad et al (2010) as well as Prasad and Puri (2005) studies, the KPP model is tested further to predict financial distress in various industries – both in terms of its accuracy of bankruptcy prediction, and, in terms of the model providing early warning signals.

THE 'KPP' MODEL: A WARNING SIGNAL?

As mentioned earlier, the KPP model combines expertise and judgement to the prediction of corporate failure through the application of an analytic hierarchy process to assess the risk profiles of firm failure. These assessed risk profiles are then evaluated as predictors of the onset of bankruptcy risk.

The KPP model incorporates the analytic hierarchy process (AHP) methodology introduced by Saaty [1977], and expanded in the Saaty [1987] paper. The AHP methodology is a systematic approach to model a decision situation involving multiple criteria / activities as a hierarchy of functional / structural relationships that links the overall objective at the top of the hierarchy to the activities / decision variables at the bottom of the hierarchy. The core of the solution procedure is to determine the priority weights assigned to the decision variables that are consistent with the achievement of the overall objective defined at the top of the hierarchy. The process requires a series of pair wise comparisons of criteria / activities at each hierarchy level in terms of their importance to the achievement of the criterion at the higher level of the hierarchy to which they are linked. These responses are obtained from one or more of the decision makers on a scale of 1 to 9. A response of 1 indicates equal importance of one activity relative to another, while 9 indicates that importance of the compared activities are significantly apart. Such response matrices corresponding to each hierarchy level are prepared. They are a set of reciprocal matrices of ratios of local priority weights for each activity in comparison with another. The local priority weights are recovered from these ratios by computing the normalized eigen vectors corresponding to the maximum eigen values. These local priority weights corresponding to each hierarchy level are synthesized to arrive at the composite weights for the activities at the lowest level of the hierarchy.

The strength of this methodology lies in the facility it offers to incorporate both quantitative and qualitative factors that are deemed to impact the decision situation. Furthermore, it offers a unique approach to expert assessment of relative importance of various criteria / activities in the form of response matrices. This methodology has been applied to diverse problem areas extended over a wide range of complexity and sophistication (see Saaty and Kerns [1985] for examples.).

The proposed model suggests a credit quality rating scheme that offers a framework to score the credit quality of firms at any point in time and enables charting of quality profiles over time to assess the scope for firm failure. The model retains the generally accepted process of credit analysis based on financial information contained in financial statement variables. Traditionally, credit analysis focuses on the assessment of firm's willingness and ability to meet the financial obligations imposed by debt contracts. Financial distress would impair the firm's ability, and in some instances its willingness, to service the contractual commitments, leading to potential bankruptcy. Credit evaluation process involves identification of factors reflecting a firm's ability and willingness to service credit, obtain information on these factors, and assess their usefulness as indicators of credit quality and predictors of firm failure. Multivariate modeling extensively used in failure prediction research leans primarily on statistical approaches, both to identify the relevant factors and their relative strengths as indicators of firm credit quality and firm failure. The AHP methodology adopted in this paper offers a distinctively different approach to the evaluation of credit quality profile and firm failure assessment. This approach facilitates the specification of factors deemed relevant in the credit quality evaluation process, the appropriate variables to measure the strength of such factors, and most importantly their importance as indicators of credit quality using expert knowledge. The solution procedure enables synthesis of expert evaluators' responses into a quantitative credit quality scoring scheme.

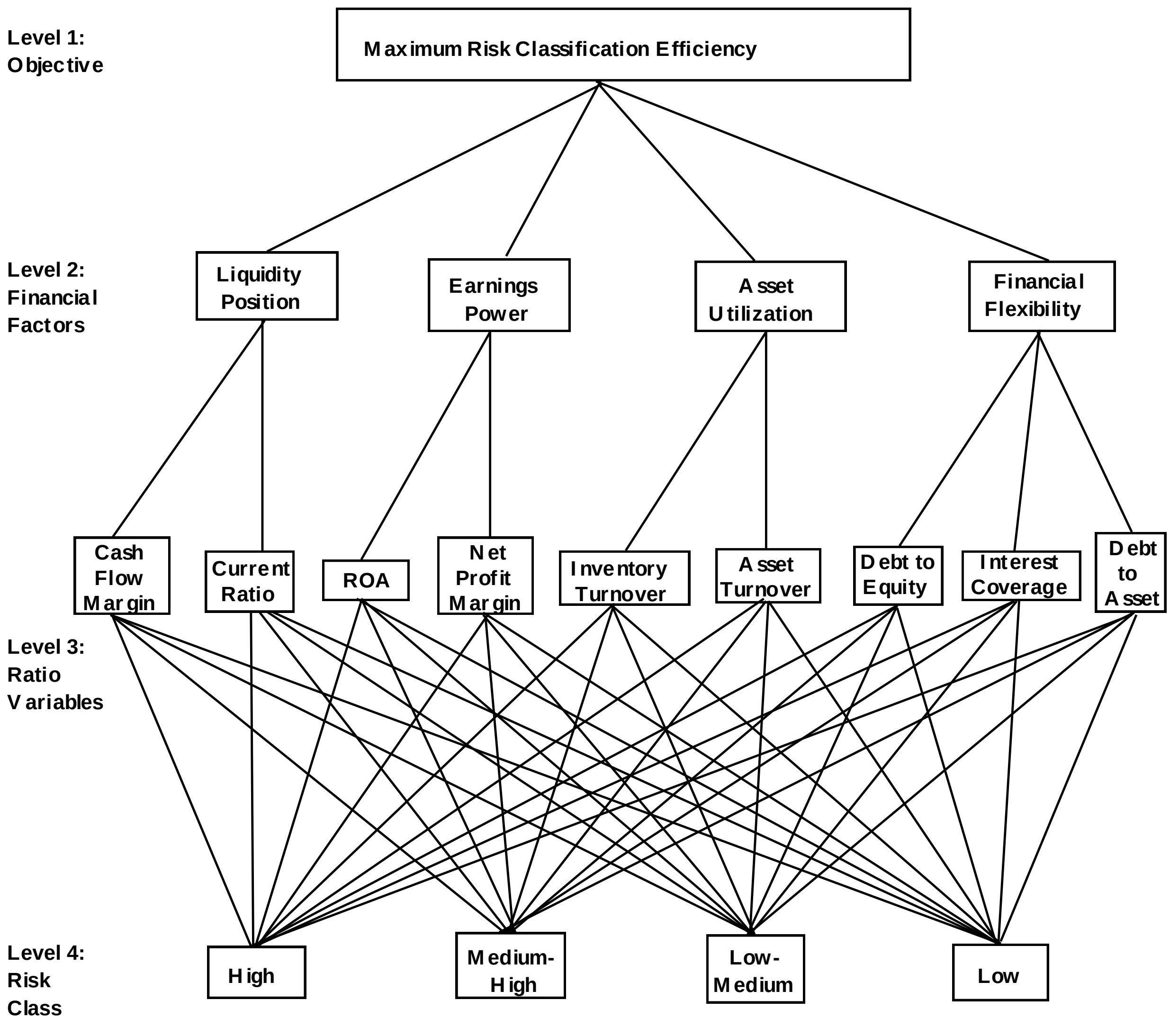
The decision problem of credit quality scoring process is modeled as a hierarchy linking the desired objective of maximal efficiency in credit quality scoring at the top of the hierarchy, to the firm's performance relative to the reference group at the bottom of the hierarchy. The hierarchical specification of the model is shown in Figure 1.

Financial factors considered relevant in forming expectations about credit risk exposure are liquidity position (LQ), earning power (EP), asset utilization (AU), and financial flexibility (FF). The choice of factors is guided by the time-honored traditions in the practice of credit evaluations, as commonly understood. This set of factors form hierarchy level 2.

Selected financial statement variables used to assess the strength of respective financial factors form hierarchy level 3. Liquidity position is assessed using current ratio (CR) and cash flow margin (CFLM); earnings' power is measured by net profit margin (NPM) and return on assets (ROA); asset utilization is measured by inventory turnover (INVX) and total asset turnover (ATT), and financial flexibility is assessed by earnings coverage of interest charges (CBT), debt to asset (DAT), and debt to equity ratios (DSE). The choice of the statement variables is governed by the need for parsimony in variable selection, and ready availability of data over the study period in the Compustat data source.

Credit quality assessment is a relative concept. A firm's credit quality is better, same, or worse than that of a reference firm or group of firms. At one extreme high levels of firm's performance on level 3 variables as measured by the respective financial ratios (in relation to the reference group) would be rated as high quality or low credit risk. At the other extreme when the quality rating is low, credit risk will be rated high.

FIGURE 1
KPP HIERARCHY MODEL



While a range of performances are possible, in our model we specify high, medium-high, low-medium, and low as performance classes relative to the reference group. These performance classes would correspond to credit (failure) risk categories low, low-medium, medium-high, and high.

The KPP model presented above provides a structure to arrive at a credit (failure) risk scoring scheme. The solution procedure is discussed below.

Credit Quality Risk Scoring Scheme

The overall credit quality scores are computed using a series of response matrices for each hierarchy level and a synthesizing process. The response matrix for hierarchy level 2 in Table 1 represents expert evaluators' scores about the relative importance of factors taken in pairs.

For example, the responses in the second row of the matrix indicate that the earnings power is significantly more important (4) than asset utilization, relatively more important (3) than liquidity, and moderately more important (2) than financial flexibility in determining the likelihood of bankruptcy.

TABLE 1
COMPARISON OF LEVEL 2 FACTORS: RESPONSE MATRIX FOR FINANCIAL FACTORS

	LQ	EP	AU	FF	Weights
LQ	1.00	0.25	2.00	0.25	0.13
EP	3.00	1.00	4.00	2.00	0.47
AU	0.50	0.25	1.00	0.50	0.11
FF	4.00	0.50	2.00	1.00	0.30

The priority weights of the factors are the elements of the normalized eigen-vector computed from the matrix using the geometric approximation technique [Saaty and Kerns [1985], p.32]. These weights are in the last column of Table 1. As can be noted, in the context of the overall objective of understanding of bankruptcy risk, earnings power and financial flexibility account for more than 70% of the total weight.

From a set of four response matrices corresponding to hierarchy level 3, the priority weights for the statement variables as measures of the associated level 2 factors are computed. For example, using the response matrix for earnings power shown in Table 2, the priority weights for net profit margin and return on assets are computed to be 0.17 and 0.83, respectively.

TABLE 2
COMPARISON OF LEVEL 3 VARIABLES: RESPONSE MATRIX FOR EARNINGS POWER

	NPM	ROA	Weights
M	1.00	0.20	0.17
A	5.00	1.00	0.83

This table indicates that for the expert evaluator, the return on assets (ROA) variable is significantly (5) more important that net profit margin (NPM) as a measure of earnings power. Similar procedure is followed in arriving at priority weights for the rest of the statement variables in level 3. Table 3 lists the weights for sets of hierarchy level 3 variables.

TABLE 3
WEIGHTS FOR HIERARCHY LEVEL 3 VARIABLES: SUMMARY OF RESPONSE MATRICES FOR LIQUIDITY, EARNINGS POWER, ASSET UTILIZATION, AND FINANCIAL FLEXIBILITY

LQ	Weights	EP	Weights	AU	Weights	FF	Weights
CR	0.14	NPM	0.17	INVX	0.33	CBT	0.55
CFLM	0.86	ROA	0.83	ATT	0.67	DAT	0.26
						DSE	0.29

Hierarchy level 4 credit risk (performance) classes are prioritized using the pair wise comparison matrix in Table 4.

The responses for example indicate that (according to the respondents) an assessment of a high credit risk reflected by the low performance of the firm relative to the reference group is highly significant (9) in comparison with low credit risk reflected by high performance. The priority weights are adjusted to reflect the categorical nature of the performance classification by assigning proportionate values relative to the risk class scoring the highest normalized priority weight [See Saaty [1987]). The fractional weights are scaled by 100.

TABLE 4
WEIGHTS FOR HIERARCHY LEVEL 4:
RESPONSE MATRIX FOR CREDIT RISK CATEGORIES

	Low	Low- Medium	Medium-High	High	Weights
Low	1.00	0.333	0.25	0.11	7.78
Low-Medium	3.00	1.00	0.25	0.14289	14.35
Medium-High	4.00	4.00	1.00	0.25	35.49
High	9.00	7.00	4.00	1.00	100.00

TABLE 5
COMPOSITE CREDIT QUALITY SCORES

	Low	Low-Medium	Medium-High	High
CR	0.14	0.25	0.63	1.76
CFLM	0.84	1.56	3.85	10.84
NPM	0.62	1.14	2.83	7.97
ROA	3.03	5.59	13.82	38.93
INVX	0.27	0.50	1.24	3.50
ATT	0.55	1.02	2.52	7.10
CBT	1.28	2.37	5.86	16.50
DAT	0.61	1.11	2.77	7.80
DSE	0.68	1.25	3.01	8.70
Sum	8.02	14.79	36.59	103.10

The overall credit (failure) risk-score class is computed by multiplying the respective priority weights. These are shown in Table 5. Note that a higher score is assigned to indicate a lower credit quality or higher failure risk. For example, the total risk score of 38.93 corresponding to ROA and high risk is assigned when firm's earning's performance measured by ROA is low. This composite risk score is obtained by multiplying the weights for earnings power (0.47 from Table 1), ROA (0.83 from Table 2), and high risk (low performance) weight (100 from Table 4).

Firm Credit Quality Risk Profile

For this study firms in seven industries were selected. The choice of industry was mostly guided by the data availability of failing firms in each industry. The criteria were to pick those industries which had a reasonable number of bankrupt firms with data for at least five years prior to the date of bankruptcies during the turbulent study period of 1980-90 in the research file of Compustat database.

For each industry a reference group of ongoing firms from the current files of the Compustat data base are identified. Table 6 shows the basic criteria for inclusion of a firm in the reference group.

TABLE 6
CRITERIA FOR INCLUDING A FIRM IN THE REFERENCE GROUP

Variable	Criterion
Cash Flow Margin	Greater Than Zero for Five Years
Net Profit Margin	No Two Consecutive Negative Values
Debt to Assets	Non Negative
Debt to Equity	Non Negative

Accordingly, the first step in scoring credit quality of firms is the computation of the means, and standard deviations for each of the level 3 financial variables for the period 1975 to 1990 for the reference group of firms in the respective industries. Performance of the firm selected for the profile analysis is compared with the reference group mean for its industry, and a KPPz-score is computed to locate its relative position.

TABLE 7
RATING RULES FOR LIQUIDITY, EARNING POWER, ASSET UTILIZATION, AND FINANCIAL FLEXIBILITY

Firm Performance Level	Credit Risk Levels	KPPz Score Intervals
High	Low	+0.675 < KPPz
Medium-High	Low-Medium	-0.675 < KPPz < +0.675
Medium	Medium-High	-1.280 < KPPz < -0.675
Low	High	KPPz <-1.280

The KPPz-score on each variable is used to rate the firm's relative performance as high, medium-high, low-medium, or low. The rating rules for variables reflecting liquidity position, earnings power, asset utilization, and financial flexibility is as shown in Table 7.

For Debt to Assets and Debt to Equity ratios, the risk ratings are reversed for corresponding intervals.

Credit quality score from Table 3 for each of the twenty-seven factor / variable / quality combination is obtained and summed to arrive at the total credit quality score for the firm. Profiles for failed firms are obtained by computing the scores for at least five years including the year of bankruptcy. A total of 43 ongoing firms and 55 failed firms in 7 industry groupings were scored and profiles generated for analysis.

Analysis of Quality Score Profiles

One of the objectives of the paper is to show that the framework presented here offers a unique approach to develop numerical credit quality scores based on expert evaluation rather than purely statistical analysis of past data. The risk scores generated by the proposed modeling approach are analyzed for information content as measures of firm credit quality / firm failure indicators in the following discussion. As noted earlier a representative sample of ongoing firms and bankrupt firms in seven selected industries were scored and profiles generated for this analysis. Typical default scores and risk profiles for firms in the Crude Petroleum and Natural gas industry (SIC: 1311) are presented in Tables 8 and 9, and Figures 2 and 3 respectively.

From the scoring scheme in Table 3, it can be noted that a remarkably healthy firm, with exceptional quality performance indicated by all the ratios measured would have a cumulative failure risk score as low as 8.02. At the other extreme very poor performance will be scored as high as 103. Low-Medium, and Medium-High failure scores are 14.8, and 36.6 respectively. The scoring process is clearly geared to reducing the Type 2 error of scoring a failing firm as a healthy firm. The cost incurred is the increase in Type 1 error of scoring a healthy firm as a high risk firm. The classification error would of course depend on the cutoff failure risk score chosen. Based on the scheme a simple test procedure to evaluate the information content of the scores would be to look at the classification rates for class intervals 8-15, 15-37, and 37-103 among the reference group firms and bankrupt firms. The 37-103 group contains medium-high and high risk category firms. Table 8 shows that most scores for bankrupt firms fell in this range, while Table 9 shows that most scores for the reference group of firms were below this range. Similarly, Figure 2 shows the clustering of the scores of the bankrupt firms in the 37-103 range and Figure 3 shows the clustering of the reference group forms in the low score range.

TABLE 8
SCORE PROFILES FOR BANKRUPT FIRMS IN SIC 1311: CRUDE PETROLEUM AND NATURAL GAS INDUSTRY

TIC	Years													
	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88
2272B	25	86	83	79	79	74	87	72	63					
4208B	49	83	58	41	78	71	68	80	89	73	94	89	75	93
4227B	58	58	83	78	78	78	66	74	80	80				
4268B	49	81	78	79	78	66	73	86	88	81	83	69		
4390B								79	88	72				
4497B							87	80	83	82				
4604B	13	50	56	25	57	69	71	88	89	86	82	82		
5189B						50	85	68	81	81	81	81	71	
5277B	35	23	35	74	73	72	71	88	82	83	85	79		
ABLEQ							82	80	81					
ARGN	58	47	44	42	62	71	77	24	88	83				
CRCRQ				47	72	75	90	69	66					
DIAB						26	71	62	69	79	82			
DISQE	73	79	32	71	73	79	72	78	74	78	74			
DKMNQ					63	71	90	80	83					
GAZQE										68	90	90		
GFEC		63	69	74	68	48	58	80	72					
MUTO	81	74	78	22	65	61	26	74	83	81				
OILQE						57	74	55	57	68	77	87		
PNXX						69	85	77	77	74	77	96		
SNCAQ	50	38	43	48	88	64	75	86	88					
TWEX							68	39	73	89				

TABLE 9
SCORE PROFILES FOR REFERENCE GROUP FIRMS IN SIC 1311: CRUDE PETROLEUM AND NATURAL GAS INDUSTRY

TIC	Years															
	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
CXY	29	26	21	19	46	34	34	39	43	20	32	36	31	33	78	78
EQTY	16	17	12	12	22	13	11	13	10	14	14	69	23	27	51	23
POY	13	24	15	17	22	23	18	10	10	12	12	15	13	15	23	15
PRSB							21	33	18	18	54	17	28	11	17	21
REX								52	65	79	34	20	15	15	11	15
SRB	43	44	76	41	19	27	19	15	11	12	10	10	13	15	11	15
SFY						31	22	13	29	51	26	13	11	11	11	15
WISE	11	10	14	12	9	10	11	10	10	15	16	16	27	19	11	14

This is borne out from the classification rate of reference group firms. While on the average (75-90%) are classified as ongoing, these rates reach lows in the 20% range for years 1976, 1979, 1981, and 1990. These were the years of price and production uncertainties. These were also years when larger percentages of firms in the reference group are classified as high risk. The model as noted earlier is designed to be relatively conservative. Given the scheme's propensity to type 2 error and the relative volatility of this industry, classification of a very small number of reference group firms as falling under the low or medium group is significant.

FIGURE 2
SIC 1311: BANKRUPT FIRMS RISK SCORES PROFILE CHART

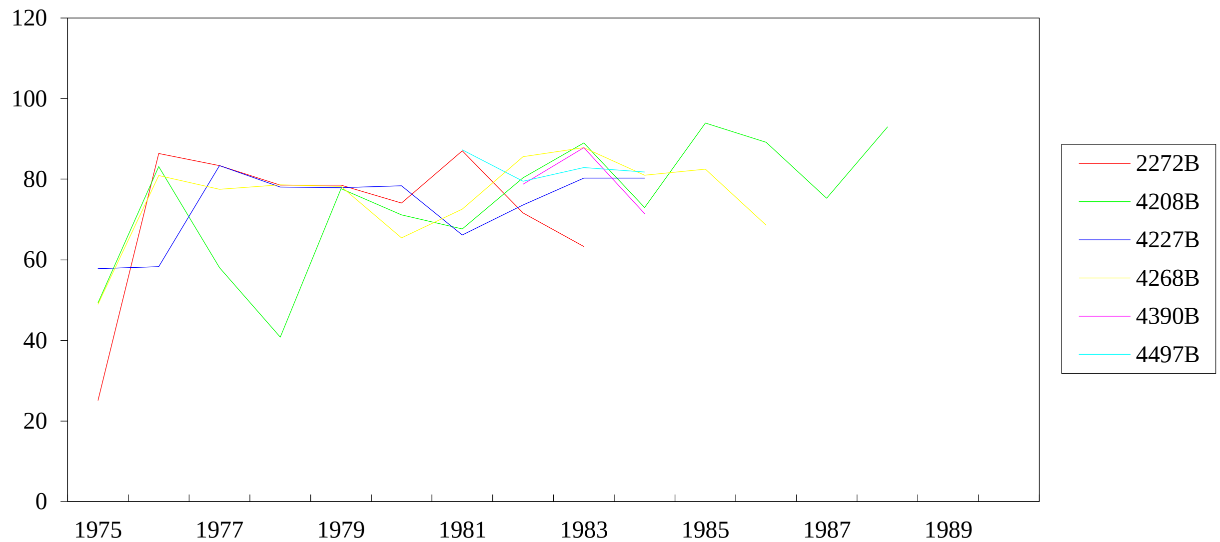


FIGURE 3
SIC 1311: REFERENCE GROUP FIRMS RISK SCORES PROFILE CHART

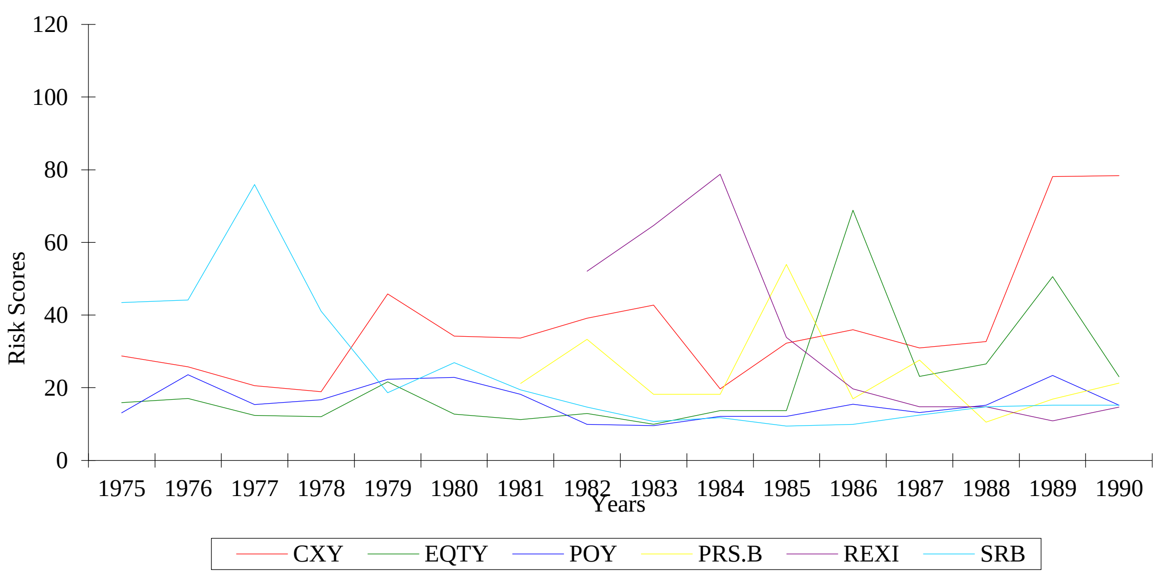


Table 10 lists the classification rates for firms in the industry 1311. Firms that failed sometime during the initial study period 1980- 1990 are included in the bankruptcy group.

The results presented in Table 10 clearly demonstrate the efficiency of the risk scores as a measure of failure risk. Firms in the bankrupt group failed during the initial study period 1980-1990; the earliest date of bankruptcy being 1983. As can be readily seen as high as 80% of this group is classified as high-risk firms even as early as 1975. The percent classified increases to 100% as the firms in the group get closer to their eventual bankruptcy. None of them are classified into the low-risk category even as early as 1976. The Crude Petroleum and Natural gas industry is a relatively high risk industry.

TABLE 10
CLASSIFICATION RATES FOR SIC 1311:
CRUDE PETROLEUM AND NATURAL GAS INDUSTRY

Years / Interval	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
Scores 8-15: Low Failure Risk Range																
%RGF[1]	40	20	40	40	20	33	29	82	72	57	43	43	50	50	38	25
%BKF[2]	10	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Scores 15-37: Medium Failure Risk Range																
%RGF	40	60	40	40	60	67	43	13	13	25	38	57	50	25	38	63
%BKF	20	9	18	18	0	6	6	6	6	0	0	0	0	0		
Scores 37-103: High Failure Risk Range																
%RGF	20	20	20	20	20	0	18	5	15	18	19	0	0	25	24	12
%BKF	70	91	82	82	100	94	94	100	100	100	100	100	100	100		
Cross Section Average Failure Risk Scores																
Years / Firms	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
RGF	22	24	28	20	23	23	20	23	24	28	25	25	20	18	27	25
BKF	49	62	60	57	72	65	72	74	79	78	82	84	73	93		

[1]Reference Group Firms (RGF)

[2]Bankrupt firms (BKF)

The last two rows of Table 10 list the average scores for reference group and bankrupt firms. For this study period the range of average scores for healthy firms is between 18 and 27. For Bankrupt firms the range is 49-93. The clear distinction in the scores can also be noted in the profiles in Tables 8 and 9. Most reference group firms have score profiles falling between 10 and 30. For some healthy firms the scores peak to as high as 80 but drop back to normal ranges relatively quickly and stay in the range.

For most bankrupt firms score profiles fall consistently in the range 60-90. For firm 2272B the score jumped from a 25 points in 1975 to 86 in 1976 never recovering until bankruptcy in 1983. Firm 4208B scores dropped from a high of 83 in 1976 to 41 in 1978, but moved back to above 70, indicating eventual bankruptcy in 1988. These profiles show clearly that once a firm’s failure risk score hits values above 60 points and stay there for a period of time, near term reductions in the scores are not sustainable.

In general, there is greater volatility in the risk profiles of bankrupt firms than ongoing firms. Such volatility and near term improvement in the scores are attributable in part to improvements in such ratios as cash flow margin and return on assets. Cash flow margins tend to improve even as the firm is beginning to lose market share, since in the near term rate of decline in sales tend to exceed the rate of decline in cash flows. Management effort to shore up cash flows with short term borrowing may also add to the improvement in this ratio. The adverse impact on current ratio is weighted less in relation to cash flow margin in the KPP scoring scheme. The decline in asset base, particularly current assets tend to improve the return on assets. Even marginal improvements tend to shift the risk from the high end to next lower level. In KPP model scoring scheme this reduces the risk score significantly. Such favorable shifts are temporary when the firm's market position and earnings power fail to recover. Increasing scores after near term improvements clearly indicate eventual failure in the market place leading to bankruptcy.

The KPP model was also used for bankruptcies in other industries. Analysis of the score profiles for the other industries studied also confirm the findings for SIC 1311. These additional industries studied were industry group SIC 3571: Electronic Computers and industry group SIC 5812: Eating Places

Analyses of classification rates for industry group SIC 3571: Electronic Computers and industry group SIC 5812: Eating Places are presented in Tables 11 and 12, respectively.

The classification pattern for these industries is similar to that for industry group 1311. For industry groups 3571 and 5812, relatively lesser percentage of reference group firms fall in the high-risk category while almost all the bankrupt firms are classified as high risk. The cross-sectional averages show the distinction between the bankrupt and reference group firms very clearly.

TABLE 11
CLASSIFICATION RATES FOR SIC 3571: ELECTRONIC COMPUTERS

Years / Interval	'75	'76	'77	'78	'79	'80	'81	'82	'83	'84	'85	'86	'87	'88	'89	'90
Scores 8-15: Low Failure Risk Range																
%RGF[1]		67	25	25	25	40	40	60	40	60	60	60	20	40	20	20
%BKF[2]		33	0	0	0	0	0	0	33	0	0	0	0	0	0	0
Scores 15-37: Medium Failure Risk Range																
%RGF		33	75	50	50	40	40	20	60	20	40	20	40	40	80	80
%BKF		67	33	0	0	0	0	0	0	0	0	0	0	0		
Scores 37-103: High Failure Risk Range																
%RGF		0	0	25	25	20	20	20	0	20	0	20	20	20	0	0
%BKF		0	67	100	100	100	100	100	100	100	100	100	100	100		
Cross Section Average Failure Risk Scores																
Years / Firms	'75	'76	'77	'78	'79	'80	'81	'82	'83	'84	'85	'86	'87	'88	'89	'90
RGF		31	25	28	30	27	26	25	21	26	21	25	26	26	24	22
BKF		22	56	65	77	81	82	71	67	83	84	85	80	80		

[1]Reference Group Firms (RGF)

[2]Bankrupt firms (BKF)

TABLE 12
CLASSIFICATION RATES FOR SIC 5812: EATING PLACES

Years / Interval	'75	'76	'77	'78	'79	'80	'81	'82	'83	'84	'85	'86	'87	'88	'89	'90
Scores 8-15: Low Failure Risk Range																
%RGF[1]	17	33	50	50	43	43	38	56	33	33	33	44	33	33	22	22
%BKF[2]	50	50	0	0	0	0	0	0	0	0	0	0	0			
Scores 15-37: Medium Failure Risk Range																
%RGF	67	50	33	33	43	43	63	22	56	44	56	44	44	44	56	77
%BKF	0	0	50	0	0	0	0	0	0	0	0	0	0			
Scores 37-103: High Failure Risk Range																
%RGF	17	17	17	17	14	14	0	22	11	22	11	11	22	22	22	0
%BKF	50	50	50	100	100	100	100	100	100	100	100	100	100	100		

Cross Section Average Failure Risk Scores																
Years / Firms	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
RGF	27	27	27	25	26	26	21	25	25	29	25	23	23	27	22	23
BKF	54	54	55	97	73	84	75	84	89	96	63	68	86			

[1]Reference Group Firms **(RGF)**

[2]Bankrupt firms **(BKF)**

The score profiles of bankrupt firms and selected reference group firms for industry group SIC 3571 are presented in Table 13 and 14, and those for firms in SIC 5812 are presented in Tables 15 and 16.

The risk scores for bankrupt and reference group firms in industries SIC 3571 are in Tables 13 and 14, respectively, and those for SIC 5812 are in Tables 15 and 16, respectively. These tables show that the bankrupt firms are in almost all cases identified as high-risk firms as early as four to five years prior to the date of bankruptcy.

There is a remarkable consistency in the distinction between the average failure risk scores of healthy and bankrupt firms in every industry.

TABLE 13
SCORE PROFILES FOR BANKRUPT FIRMS IN SIC 3571: ELECTRONIC COMPUTERS

	Years															
TIC	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
5761B											86	91	91			
DDSQE		27	82	78	78	83	83	58	87	87	89	94	65	84		
IDPYQ		27	70	62	83	75	77	42	103							
KPRQE								86	11	80	79	71	83	76		
QONEQ		13	16	56	69	85	84	95								

TABLE 14
SCORE PROFILES FOR REFERENCE GROUP FIRMS IN SIC 3571: ELECTRONIC COMPUTERS

	Years															
TIC	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
AMH		13	9	12	54	58	59	72	30	69	31	57	49	14	24	22
AAPL						13	11	8	10	15	15	13	13	12	8	8
CYR		70	28	34	18	20	20	19	27	14	13	17	19	23	30	17
TDM			39	23	12	14	13	13	23	14	13	13	21	51	25	30
TAN		10	26	42	34	32	28	12	12	21	34	24	27	27	33	32

TABLE 15
SCORE PROFILES FOR BANKRUPT FIRMS IN SIC 5812: EATING PLACES

	Years															
TIC	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
5282B										94	89	97	85			
6028B											31	21	85			
CHKYQ						61	30	71	97							
FMLYQ							87	97	86							

	Years															
HHI										94	68	85	87			
JIFF	94	95	81	97	49	97	97	95	92	97						
PEPLQ							65	58	80	98						
QSRI	13	13	29	97	97	95	95	97								

TABLE 16
SCORE PROFILES FOR REFERENCE GROUP FIRMS IN SIC 5812: EATING PLACES

	Years															
TIC	’75	’76	’77	’78	’79	’80	’81	’82	’83	’84	’85	’86	’87	’88	’89	’90
BOBE	12	10	10	9	9	9	13	11	11	11	11	13	13	10	11	11
FRS	68	71	46	41	40	40	28	59	69	69	75	42	29	56	25	50
LUB	18	15	12	14	10	11	14	9	10	11	11	12	11	11	11	11
MORR	15	15	16	16	16	29	29	29	24	39	27	17	18	17	17	25
PAMX	30	44	75	66	82	71	32	39	19	18	15	15	15	16	16	16
PICC					14	13	13	11	24	16	16	11	14	19	18	18
RYAN							25	14	15	11	14	9	12	13	13	13
SHEF	14	15	16	17	16	17	17	31	34	23	16	16	16	34	34	33
SHN	14	15	16	17	16	17	17	31	34	23	16	16	16	34	34	33
WEN	31	16	12	14	17	18	21	30	23	35	35	82	44	31	27	26

In addition to the data presented above for the three industry groups, the KPP model was also applied to the following industry groups: SIC 2750 – Commercial Printing; SIC 3661 – Telephone and Telegraph Apparatus; SIC 3674 – Semiconductor and Related Devices; and SIC 7373 – Computer Integrated System Design. The averages and standard deviations of the pooled cross section time series scores for each of the seven industries analyzed are presented in Table 17. The “t”-stats in the last column show clearly that the differences in the mean scores of bankrupt and reference group firms are highly significant. The expert system based scores are excellent discriminators of failing firms.

TABLE 17
POOLED CROSS SECTION TIME SERIES FAILURE RISK SCORES INDUSTRY DATA

INDUSTRY	REFERENCE GROUP FIRMS RISK SCORES		BANKRUPT FIRMS RISK SCORES		MEANS TEST
SIC Code	Average	STDEV	Average	STDEV	“t”-Stat
1311	23.40	16.28	70.58	16.64	23.42
2750	26.47	19.56	76.53	20.10	10.65
3571	25.15	15.94	71.15	23.77	11.99
3661	25.89	17.33	85.01	18.84	12.92
3674	22.98	16.73	71.86	22.34	12.57
5812	24.53	18.34	76.42	27.17	13.47
7373	24.01	16.88	61.42	29.84	7.07

CONCLUDING COMMENTS

The study presents the KPP model as an expert systems model which can act as an alternative to traditional statistical approaches to the prediction of corporate failure. The analytic hierarchy process methodology adopted in the KPP model is eminently suited for the incorporation of expert evaluation of both qualitative and quantitative factors deemed appropriate in the assessment of financial distress leading to bankruptcy. It provides full scope for the use of credit evaluation professionals' expert knowledge in assessing the information content of financial statement variables that are not precise and often are volatile. The approach further offers a structured procedure to integrate such evaluations and arrive at numerical risk scores that can be validated.

The study analyzed bankruptcies in seven disparate industries over the 1975-90 period and presented evidence on the information content of the risk scores as predictors of financial distress and bankruptcy. In almost all cases the risk scores proved to be excellent predictors of bankruptcy as early as four or five years prior to bankruptcy. The mean scores for bankrupt firms and reference group firms are consistently far apart. The statistical significance of the differences in the mean squares is quite apparent. The risk scores in this study developed for seven disparate industries and the profiles of financial distress are consistent with test sample results. The model in this paper includes four risk categories: Low, Low-Medium, Medium-High, and High risk classes; and the computation of weights for risk category hierarchy level.

It is possible to extend the KPP model presented by including additional variables and additional hierarchies. The benefits of additional variables and/ or additional hierarchies offers scope for further research. Research is possible on how model can be customized to be user specific and provide a method to document the expert evaluation process, especially in situations where qualitative variables play a crucial role in the credit granting process. Also, further research could include comparison of this model's results with the results of obtained using the Altman, Ohlson and other models on a common data base. As suggested by the Prasad and Puri [2005] study, combining models may further increase the accuracy of the bankruptcy predictions as well as provide earlier signals of impending financial distress.

REFERENCES

Abid, F., & Zouari, A. (2003). *Financial Distress Prediction using Neural Networks*. (Unpublished working paper). SSRN Working Paper Series.

Ahn, H., & Kim, K. (2009). Bankruptcy prediction modeling with hybrid case-based reasoning and genetic algorithms approach. *Applied Soft Computing*. Elsevier.

Altman, E.I. (1968, September). Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy. *Journal of Finance*, pp. 589–609.

Altman, E.I. (1971). *Corporate Bankruptcy in America*. Lexington, Massachusetts: Heath.

Altman, E.I. (1981). Application of Classification Techniques in Business, Banking, and Finance. Greenwich, Connecticut: JAI Press.

Altman, E.I. (1995). Failure Prediction: Evidence from Korea. *Journal of International Financial Management and Accounting*, *6*(3).

Altman, E.I. (2018). Applications of Distress Prediction Models: What Have We Learned After 50 Years from the Z-Score Models. *International Journal of Financial Studies*, *6*(70), 1–15.

Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. Expert Systems With Applications. Elsevier.

Beaver, W.H. (1966). Financial Ratios as Predictors of Failure. *Empirical Research in Accounting*: *Selected Studies*.

Begley, J., Ming, J., & Watts, S.G. (1997). Bankruptcy Classification Errors in the 1980s: An Empirical Analysis of Altman's and Ohlson's Models. *Review of Accounting Studies*, *1*(4).

Boston Globe. (2004, January 6). *Enron seeks $43.2m bonus OK.*

Charalambous, C., Charitou, A., & Kaourou, F. (2000). Comparative analysis of artificial neural network models: Application in bankruptcy prediction. *Annals of Operations Research*. Springer.

Clark, C.E., Foster, P.L., Hogan, K.M., & Webster, G.H. (1997). Judgmental Approach to Forecasting Bankruptcy. *Journal of Business Forecasting*, *16*(2), 14–18.

Curry, T.J., Fissel, G.S., & Elmer, P.J. (2002). *The Behavioral/ Contracts Theory of the Corporate Entity and Financial Distress*. (Unpublished working paper) SSRN Working Paper Series.

Dambolina, I.G. (1983). The Prediction of Corporate Failures. *OMEGA*, pp. 355–364.

Dambolina, I.G., & Khoury, S.J. (1980, September). Ratio Stability and Corporate Failure. *Journal of Finance*, pp. 1017–1076.
Edminster, R.O. (1972, March). An empirical test of financial ratio analysis for small business failure prediction. *Journal of Financial Quantitative Analysis*, pp. 1477–1493.
Expert Choice. (1992). *Virginia*. Decision Support Software, Inc.
Fitzpatrick, P.J. (1932, October, November, & December). A Comparison of ratios of successful industrial enterprises with those of failed firms. *Certified Public Accountant*, pp. 598–605, pp. 656–662, pp. 727–731.
Henebry, K.L. (1996). Do Cash Flows Improve the Predictive Accuracy of a Cox Proportional Hazards Model for Bank Failure. *Quarterly Review of Economics and Finance*, *36*(3).
Jones, F.L. (1987). Current Techniques in Bankruptcy Prediction. *Journal of Accounting Literature*, pp. 131–164.
Leclere, M.J. (2002). Time-Dependent and Time-Invariant Covariates Within a Proportional Hazards Model: A Financial Distress Application. Working Paper, SSRN Working Paper Series.
Lev, B. (1974). *Financial Statement Analysis: A New Approach*. Englewood Cliffs, New Jersey: Prentice Hall.
McKee, T.E. (2003). Rough sets bankruptcy prediction models versus auditor signaling rates. *Journal of Forecasting*. Wiley Online Library.
Min, J.H., & Jeong, C. (2009). A binary classification method for bankruptcy prediction. *Expert Systems With Applications*. Elsevier.
Min, S.H., Lee, J., & Han, I. (2006). Hybrid genetic algorithms and support vector machines for bankruptcy prediction. *Expert Systems With Applications*. Elsevier.
Nam, J.H., & Jinn, T. (2000). Bankruptcy Prediction: Evidence from Korean Listed Companies during the IMF Crisis. *Journal of International Financial Management and Accounting*, *11*(3).
Norton, C.L., & Smith, R.E. (1979, January). A Comparison of general price level and historical cost financial statements in the prediction of bankruptcy. *Accounting Review*, pp. 72–86.
Nwogugu, M. (2003). The Behavioral/ Contracts Theory of the Corporate Entity and Financial Distress. (Unpublished Working Paper). SSRN Working Paper Series.
Ohlson, J. (1980, Spring). Financial Ratios and Probabilistic Prediction of Bankruptcy. *Journal of Accounting Research*, pp. 109–131.
Pindado, J., & Rodrigues, L. (2001). Parsimonious Models of Financial Insolvency in Small Companies. (Unpublished Working Paper). SSRN Working Paper Series.
Prasad, D., & Puri, Y.R. (2005). Does Combining Alternate Bankruptcy Prediction Models Improve Forecasting Accuracy? *International Journal of Finance*, *17*(3), 3581–3602.
Prasad, D., Puri, Y.R., & Jain, R. (2010). Could Investors' Wealth Have Been Saved Using Bankruptcy Prediction Models to Forecast The 24 Largest Bankruptcies? *International Journal of Accounting Information Science and Leadership*, *3*(6).
Ramser, J.R., & Foster, L.O. (1931). *A Demonstration of Ratio Analysis*. University of Illinois, Urbana: Bull Bureau of Business Research.
Saaty, T.L. (1977). A Scaling Method for Priorities in Hierarchical Structures. *Journal of Mathematical Psychology*, pp. 223–281.
Saaty, T.L. (1987). Concepts, Theory and Techniques: Rank Generation, Preservation, and Reversal in Analytic Hierarchy Decision Process. *Decision Sciences*, pp. 157–177.
Saaty, T.L., & Kerns, K.P. (1985). *Analytical Planning: The Organization Systems*. New York: Pergammon Press.
Santomero, A., & Vinso, J. (1977, September). Estimating the probability of failure for firms in the banking system. *Journal of Banking and Finance*, pp. 185–205.
Scott, J. (1981, September). The probability of bankruptcy: A comparison of empirical predictions and theoretical models. *Journal of Banking and Finance*, pp. 317–344.
Theodossiou, P., & Kahya, E. (1999) Predicting Corporate Financial Distress: A Time-Series CUSUM. *Review of Quantitative & Finance Accounting*, *13*(4), 323–345.

Wasserman, J. (2003, December 28). State treasurers put heat on Wall Street. *Boston Sunday Globe*, p. A28.

White, R.W., & Turnbull, M. (1975). *The Probability of bankruptcy: American Railroads*. (Unpublished Working Paper). Institute of Finance and Accounting, London University Graduate School of Business.

Wilcox, J.W. (1971, September). A gambler's ruin prediction of business failure using accounting data. *Sloan School Management Review*, pp. 1–10.

Winaker, A.H. & Smith, R.F. (1935). *Changes in financial structure of unsuccessful industrial corporations*. Bull, Bureau of Business Research, University of Illinois, Urbana.

Yu, Q., Miche, Y., Séverin, E., & Lendasse, A. (2014). Bankruptcy prediction using extreme learning machine and financial expertise. *Neurocomputing*. Elsevier.

Zevgren, C. (1983). The Prediction of Corporate Failure: The State of the Art. *Journal of Accounting Literature*, pp. 1–38.