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UNDERSTANDING DIFFERENCES BETWEEN FINANCIAL DISTRESS AND BANKRUPTCY

Harlan D. Platt [*] **&** ***Marjorie B. Platt*** [**]

For the most part, research purporting to address the issue of financial distress has actually studied samples of bankrupt companies. Financial distress and bankruptcy are different. In contrast, this paper starts with a sample of companies that are financially distressed but not yet bankrupt. The sample is obtained by screening the Compustat industry database with a three-tiered identification system. The screen separated companies into financially and non-financially distressed groups. A multi-tiered screen reduces the incidence of mistakenly identifying a non-distressed company as financially distressed. The paper then compares factors indicating the likelihood of future bankruptcies to those indicating future financial distress. To do this, an early warning financial-distress model is developed and compared to a methodologically similar existent model of bankruptcy. The final financial distress model includes only one variable present in the bankruptcy model and four new variables. The limited overlap of explanatory factors between the models questions the similarity of financial distress and bankruptcy. Statistical tests lend support to the notion that the bankruptcy process is not just a continuation of a downward spiraling cycle of financial distress. We infer that financial distress is something that happens to companies as a consequence of operating decisions or external forces while bankruptcy is something that companies choose to do to protect their assets from creditors.

JEL Classifications*: G 30, G33*

Keywords*: financial distress, early warning model, renewal*

INTRODUCTION

Codification of the major determinants of corporate bankruptcy, such as Altman (1968), enables stakeholders such as bank loan officers, investors, credit managers, regulators and vendors among others to reduce their financial risks. These benefits principally accrue to participants in the end-stage of the corporate life cycle. That is, these predictions come too late in the process of corporate decline to do much more than give a warning that the final phase of corporate existence is near. Thus, bankruptcy prediction provides little time for managers or boards of directors to turn around a business in crisis or financial distress.

In most cases, bankruptcy occurs subsequent to a period of financial distress. Identification of healthy companies likely to become financially distressed will allow remedial actions to

* Professor of Finance, 413 Hayden, Northeastern University, Boston, MA, *E-mail: h.platt@neu.edu*

** Professor and Group Coordinator of Accounting, 404 Hayden Hall, Northeastern University, Boston, MA, *E-mail: m.platt@neu.edu*

possibly correct the causes of corporate decline. In addition to benefiting the stakeholders listed above, earlier financial distress information will provide insights to managers and owners, and will increase confidence that future deliveries will be made among companies interrelated through corporate supply chains. Such information will enable financially distressed companies to be treated and possibly cured rather than left to fail. Moreover, understanding how financial distress and bankruptcy differ will help identify which cases of financial distress are likely to become cases of bankruptcy.

The definition of financial distress is less precise than the legal actions that define proceedings such as bankruptcy or liquidation. Despite this ambiguity, it is clear that the condition of being financially distressed deviates from corporate normality. Financial distress precedes virtually all bankruptcies except those due to sudden and unexpected events such as natural disasters, changed government regulations, or legal judgments. The question naturally arises whether the same factors known to be indicators of future bankruptcies are also indicators of future cases of financial distress and vice versa. Conceptually the question is whether financially distressed firms that evolve into bankruptcies follow their original path or whether they deviate onto a new path which leads them to bankruptcy. If they do follow their original path, variants of bankruptcy prediction models could yield financial distress predictions; alternatively, if variables that predict bankruptcy have no predictive power regarding financial distress then a completely new explanatory model is required. That inquiry is the objective of this paper.

The paper is organized as follows. Section 2 presents the literature review, Section 3 discusses the methodology, Section 4 presents the results, and Section 5 discusses the implications of the findings with respect to similarities and differences between processes giving rise to financial distress and bankruptcy. Finally, Section 6 concludes the paper by summarizing the purpose and findings of this study.

LITERATURE REVIEW

The research history of bankruptcy and financial distress prediction are dissimilar. On the one hand, an abundance of bankruptcy studies since the initial breakthroughs by Beaver (1966) and Altman (1968) consider virtually every aspect of the topic. More recent bankruptcy-prediction innovations include the use of industry-relative ratios (Platt and Platt, 1991) and methodological extensions such as neural networks (Altman, Marco and Varetto, 1994; Yang, Platt and Platt, 1999). A variety of other studies look at particular industries, countries, and alternate time periods. The topic is now fairly well understood.

On the other hand, models to predict financial distress are less common (Schipper, 1977; Lau, 1987; Hill *et al.*, 1996; Platt and Platt, 2002). Of these studies, the first looks at troubled private colleges, the second and third compare multiple states of corporate decline of which one was financial distress, and the last builds a model to predict financial distress among auto suppliers. No prior study presents a multi-industry model of financial distress. Further, no research has compared the components of financial distress to bankruptcy predictors in an industry-relative setting.

Combining many industries within a data set increases sample size, which produces econometric advantages resulting from smaller standard errors of estimates. But coefficients may not be stable across industries, which leads to a proliferation of coefficient estimates if industry specific coefficients are estimated. The industry-relative framework is one way to deal with the flexible coefficients problem and provides practical advantages arising from the use of a common platform to predict an event across many industries. Altman and Izan's (1984) pioneering work on industry-relative ratios normalizes differences among Australian industries in a bankruptcy study. Platt and Platt (1990, 1991) illustrate the conceptual benefits from using industry-relative ratios within the context of early warning system models and demonstrate the applicability of this framework using US firms. This paper uses the industry-relative framework as well but for financial distress prediction.

Most prediction studies with the words financial distress in their title actually model bankruptcy, (Frydman, Altman and Kao, 1985; Theodossiou, Kahya and Philippatos, 1996; Lin, Ko and Blocher, 1999). Other corporate distress studies examine financial restructurings (Gilson, John & Lang, 1990; Wruck, 1990; Brown, James & Mooradian, 1992) or management turnover during distress (Gilson, 1989). By contrast, the current study seeks to identify factors that differentiate firms in financial distress from those who are in a strong financial condition.

No accepted definition of financial distress has emerged from prior research. Each study adopts its own definition. Among the methods of financial distress employed by others are:

- Evidence of layoffs, restructurings, or missed dividend payments, used by Lau (1987). This approach focuses on nonfinancial and stockholder-related actions taken to preserve critical company assets.
- A low interest coverage ratio, used by Asquith, Gertner and Scharfstein (1994). This definition suggests companies may soon be technically insolvent; that is, unable to pay interest or principle on its debt.
- Cash flow less than current maturities of long-term debt, used by Whitaker (1999). This method raises questions of how current debt will be paid.
- The change in equity price or a negative EBIT, used by John, Lang, and Netter (1992). Changes in stock prices have been shown to be predictive of financial condition (Queen and Roll, 1987). Negative operating profits raises questions of long term viability of operations.
- Negative net income before special items, used by Hofer (1980). Failure to earn funds sufficient to pay interest obligations raises questions about long term solvency.

Each metric is intuitive and yet undoubtedly generates some amount of measurement errors in the dependent variable. The lack of an exact financial distress definition jeopardizes the validity of research studies because measurement errors place some non-distressed companies into the financially distressed category while also putting some financially distressed companies into the non-distressed group. Coefficient estimation becomes inconsistent with measurement error in the dependent variable (Hausman, *et al*, 1991). Without a precise definition of financial distress it is impossible to alleviate this problem. A partial solution, which is employed here, relies on a multidimensional screen for financial distress that combines several of the metrics noted above. In doing so, the probability of measurement error of the dependent variable should be reduced.

METHODOLOGY

Sample Selection and Financial Distress Identification

The study includes firms from the 2000 COMPUSTAT Industrial Annual tape that belong to the 14 manufacturing industries listed in Table 1. Restricting the data to a single year circumvents estimation issues arising from variations in inflation rates, interest rates, and GDP growth rates as described by Mensah (1984) and Platt, Platt and Pedersen (1994). The sample includes every company listed on the COMPUSTAT tape for the 14 industries to avoid choice-based sample bias (See Zmijewski, 1984). Further, the industry-relative approach used to create financial ratios for companies within the 14 industries insures a more than adequate sample size.

Table 1
Distressed and Not Distressed Companies in 14 Industries

Industry SIC Code	*Industry Name*	*Number of Companies in Financial Distress*	*Number of Companies not in Financial Distress*	*Percentage of Companies in Financial Distress*
2200	Textile Mill Products	4	19	17%
2300	Apparel & Other Textile	6	54	10%
2600	Paper & Allied Products	2	62	3%
2800	Chemicals	13	79	14%
2900	Petroleum & Coal	3	27	10%
3000	Rubber	9	68	12%
3100	Leather	2	19	10%
3200	Stone, Clay, Glass & Concrete	1	35	3%
3300	Primary Metals	10	88	10%
3400	Fabricated Metals	6	79	7%
3500	Industrial Machinery & Equipment	72	164	31%
3600	Electrical & Electronic Equipment	39	199	16%
3700	Transportation Equipment	1	18	5%
3800	Instruments & Related Products	108	216	33%
	Total	276	1,127	

Companies on the COMPUSTAT tape are separated into financially distressed and non-financially distressed groups with a three-part system, over a two-year period, 1999 to 2000. Financial distressed firms are defined as those that met each of the following screening criteria for both years.

- Negative EBITDA covering interest expense[1] (similar to Asquith, Gertner and Scharfstein (1994)).
- Negative EBIT (similar to John, Lang, and Netter (1992)).
- Negative net income before special items (similar to Hofer (1980)).

To avoid defining companies as financially distressed based on a single year of poor performance, the three screens above are calculated for the years 1999 and 2000.[2] Companies are categorized as financially distressed if all three screens were negative in both years; otherwise, companies are defined as non-financially distressed. This approach yields a total of 1,403 companies for the analysis sample, including 276 financially distressed firms and 1,127 non-financially distressed companies.[3]

Table 1 shows the distribution of financially distressed and non-financially distressed firms across the 14 industries included in the sample. The requirement that companies fall below all three financial distress screen thresholds places them in a serious though not necessarily fatal phase of distress. This methodology yields relatively more cases of financial distress in the a) Industrial Machinery & Equipment and b) Instruments & Related Products industries than in the other 12 industries. Weakness in heavy industries and segments of the high-technology sectors, as indicated by the three-screen test, is consistent with reports at the time (in 2000) in the business press of declining sales, foreign competition, and plunging stock prices affecting these industries.

How the three-tiered screening method impacts the number of companies identified as financially distressed is observed in Table 2 where single and multiple screens are compared. By definition the three-screen system produces the fewest cases of financial distress because it is a distillation of companies at the intersection of individual screens. That is, requiring firms to pass all three screens reduces the financially distressed set of companies because the various screens reflect different performance characteristics. The multiple screen methodology reduces the number of financially distressed companies by between 1.4 percent and 18.3 percent across the fourteen industries compared with a methodology calling firms financially distressed when any one of the screens is violated. Of the three separate screens, Screen 3 (negative net income before special items) captures the most companies, while Screen 1 (negative EBITDA covering interest expense) secures the fewest companies, for the financial distress category. Overlap between the three individual financial distress screens is less than complete, as seen in Table 2. Screen 3 is the most atypical as demonstrated by the large number of companies it calls financially distressed that are not similarly identified by the other two screens

The comparison group of 1,127 non-financially distressed companies includes all companies in COMPUSTAT in the 14 industries that are not already identified as financially distressed and that have complete data for 1999 and 2000. Financially distressed firms are arbitrarily assigned a value of 1, while healthy firms are assigned a value of 0. The ability of a model to differentiate between populations of companies is affected by the degree to which the groups differ. The continuum of corporate health has a healthy category on one side, a bankruptcy category on the other side, and financial distress in between. Consequently, the financial distress/non-financial distress pairing is more similar than is the bankrupt/healthy pairing which suggests that it should be more difficult to predict financial distress than it is to predict bankruptcy.

Independent Variables

Independent variables are created from financial statement data obtained from COMPUSTAT for the year 1998. Data from 1998 precedes by twelve months the date when companies are identified as financially distressed, which allows them to be used in constructing an early warning model of financial distress. The data selection includes typical financial statement items. Table 3 lists the specific financial items taken from Compustat and the financial ratios formed to

Table 2
Number of Companies Categorized as Financially Distressed (FD) Using Different Screening Options

	Companies defined as FD using 3-screens	*Additional companies defined as FD when using only 2-screens rather than 3-screens*			*Additional companies defined as FD when using only 1-screen rather than 2-screens*		
Industry	*S1+S2+S3*	*S1+S2*	*S1+S3*	*S2+S3*	*S1*	*S2*	*S3*
2200	4	0	0	0	0	1	1
2300	6	0	2	1	0	0	3
2600	2	0	0	0	2	0	6
2800	13	0	0	3	1	1	3
2900	3	0	0	0	0	0	0
3000	9	2	3	1	1	1	7
3100	2	0	1	0	0	0	1
3200	1	0	0	0	0	1	2
3300	10	0	2	7	0	0	11
3400	6	2	1	2	0	1	4
3500	72	5	0	7	0	2	7
3600	39	4	3	8	0	5	6
3700	1	0	0	0	0	1	1
3800	108	7	2	5	0	4	10
Total	276	20	14	34	4	17	62

where:
S1 = Negative EBITDA covering Interest Expense
S2 = Negative EBIT
S3 = Negative Net Income before Special Items

Table 3
Data and Financial Ratios Employed*

Individual Financial Items		*Financial Ratios*		
Status	*Inventories (Inv)*	*Profit Margin*	*Liquidity*	*Operating Efficiency*
Net Sales (S)	Current Assets (CA)	EBITDA/S	CA/CL	COGS/Inv
COGS	Net Fixed Assets (NFA)	NI/S	(CA-Inv)/CL	S/AR
Deprec.+Amort. (DA)	Total Assets (TA)	CF/S	WC/TA	S/TA
SGA	Accounts Payable (AP)	*Profitability*	CA/TA	AR/TA
EBIT	Notes Payable (NP)	EBITDA/TA	NFA/TA	S/WC
Interest Expense (Int)	Current Liabilities (CL)	NI/TA	*Cash Position*	S/Inv
Net Income (NI)	Long-term Debt (LTD)	EBIT/TA	Cash/CL	AR/Inv
Cash	Total Liabilities (TL)	CF/TA	Cash/DA	(AR+Inv)/TA
Accounts Receivable	Share Equity (EQ)	NI/EQ	Cash/TA	COGS/S
(AR)		*Financial Leverage*	*Growth*	SGA/S
		TL/TA	S-Growth%	(COGS+SGA)/S
Calculated Items		CL/TA	NI/TA-Growth%	DA/S
EBITDA = EBIT + DA		CL/TL	CF-Growth%	DA/EBIT
CF = NI + DA		NP/TA	***Miscellaneous***	S/CA
WC = CA - CL		NP/TL	EBIT/Int	
		LTD/TA	Int/S	
		Current LTD/TA	LTD/S	
		EQ/TA	CF/Int	
		LTD/EQ	CF/TL	

* All individual items were gathered for 1997 and 1998. All financial ratios were calculated for 1998. All growth variables were calculated with respect to 1998.

measure profitability, liquidity, operational efficiency, leverage and growth. These ratios are tested as possible determinants of financial distress.

The transformation of company ratios into industry-relative ratios is described in equation (1) where firm i is a member of industry j and 100 adjusts percentage ratios to scalar values greater

$$\text{Industry - Relative Ratio}_{\text{i,j}} = \frac{\textit{Firm i's Ratio } (r)}{\textit{Mean Ratio in Industry }_j} * 100 \tag{1}$$

than 1.0. The transformation starts with a company's ratio and then divides that quotient by the value of that same ratio for the average firm in the industry.[4] Industry-relative ratios combine changes occurring at individual companies and across their aggregate industry. They reveal when a company's ratio deviates from its industry norm. Industry-relative advocates such as Lev (1969) and Platt and Platt (1991) argue that these ratios are more stable and result in less disparity between ex ante and ex post forecasts. They also provide a conceptual framework in which each industry does not require a unique set of parameter estimates. Throughout the paper, industry-relative notation is suppressed to simplify notation.

Model Specification

Initially, one ratio from each group in Table 3 is selected to minimize potential multicollinearity. Because several variables in each category can potentially discriminate between the two groups of firms, various combinations of predictors across the eight categories are tested. It is expected that financial distress should be negatively related to profit margin, profitability, liquidity, growth and operating efficiency. Alternatively, financial distress should be positively related to operating or financial leverage.

A core group of predictors is developed to which additional predictors are added in an iterative process. The core set of variables expands as additional factors yield a coefficient with the expected sign, statistical significance, and improved classification accuracy. This approach concentrates on the explanatory power of variables. The selection of the final set of financial and operating ratios is based on their conformity to a priori sign expectations, the statistical significance of estimated parameters and on model classification results.

Statistical Analysis

Model building efforts utilize logit regression analysis because of its flexibility and statistical power in modeling (McFadden, 1984; Lo, 1986). A non-linear maximum-likelihood estimation procedure obtained estimates of the parameters of the logit model shown in equation (2).

$$P_i = \frac{1}{[1 + \exp^{-(B_0 + B_1 X_{i1} + B_2 X_{i2} + \ldots + B_n X_{in})}]} \tag{2}$$

where: P_i = probability of financial distress of the i^{th} firm,

X_{ik} = k^{th} variable of the i^{th} firm, and

B_k = estimated coefficient for the k^{th} variable.

The final set of variables is arrived at iteratively as described above.

RESULTS

Predictive Model of Financial Distress

The final model, shown in equation (3)[5] and Table 4, contains five variables representing profit margin, profitability, leverage, and liquidity.

$$\Pr(FD) = -4.28 - 0.128(CF/Sales) - 2.484(EBITDA/TA) + 0.123(CLTD\ Due/TA) - 0.084(TIE) + 0.269(QR) \quad (3)$$

where:
- Pr(FD) = Probability of Financial Distress
- CF/Sales = Cash Flow/Sales, a measure of profit margin[6]
- EBITDA/TA = Earnings before interest, tax, depreciation and amortization / Sales, a measure of operating profitability
- CLTD Due/TA = Current portion of long term debt due / Total assets, a measure of leverage
- TIE = Times interest earned [basically earnings before tax / interest expense], a measure of leverage
- QR = Quick ratio [(Current assets–inventories) / Current liabilities, a measure of liquidity

All estimated coefficients have the expected signs. With financially distressed firms arbitrarily coded as 1, negative (positive) coefficients describe an inverse (direct) relationship with financial distress. Higher cash flows (Cash Flow/Sales and EBITDA/TA) and greater times interest earned (Times Interest Earned) reduce the risk of financial distress; whereas, higher leverage (Current Debt Due/TA) and greater liquidity (Quick Ratio) increase the risk of financial distress. For example, the coefficient estimated on the quick ratio indicates that the risk of financial distress rises with the quick ratio. This suggests that a company that puts more of its assets into less profitable current assets versus fixed assets is at a greater risk of financial distress within the next twelve months.

The financial distress prediction model had an overall correct classification rate of 93.2 percent, as shown in Panel B of Table 4. For the distressed group, the model correctly classified 87 percent of companies; for the non-distressed group, 94.8 percent of companies. The model was also subjected to subsequent testing based on private company data supplied by BBK, Ltd. The test involved evaluating eight companies not in the estimation sample. Of the eight companies, the model successfully predicted that three (3) companies were indeed healthy and the five (5) companies that were in fact financially distressed. A total of four industries were represented in the blind validation test.

STATISTICAL COMPARISONS

Single Versus Multiple Financial Distress Screens

Before comparing financial distress to bankruptcy, a test is conducted to validate the three-screen approach for identifying financially distressed firms. The validation test is performed by

Table 4
Final Industry-Relative Early Warning Financial Distress Model

Panel A. Variables in the Final Early Warning Model

Variables	*Scaled Coefficient**	*p-value (two-tail)*
CF/Sales	-0.128	.005
EBITDA/TA	-2.484	.000
CLTD Due/TA	0.123	.005
TIE	-0.084	.075
QR	0.269	.033
Constant	-4.280	.000

* Coefficients are uniformly scaled to maintain their intrinsic meaning without revealing their actual values because they remain the property of BBK, Ltd.

where:

Name	*Definition*
CF/Sales	Cash Flow to Sales (Net Income + depreciation + amortization)/Net Sales
EBITDA/TA	Earnings before interest, tax, depreciation and amortization/Total assets
CLTD Due/TA	Current portion of long-term debt/Total assets
TIE	Times Interest Earned [(Net Income +/-discontinued operations income/expense +/ -extraordinary gains/losses +/- cumulative effect of accounting changes +/- tax benefits/expenses +/- minority interest + interest expense)/interest expense]
QR	Quick Ratio [(Current Assets – Inventories)/Current Liabilities]

Panel B: Model Classification Results

Classification Group	*Percent Correctly Classified*
Financially Distressed Firms (n = 276)	87.0%
Non financially Distressed Firms (n = 1,127)	94.8%
All Firms (n = 1,403)	93.2%

first creating alternative data sets for the 14 industries with COMPUSTAT data based on single and two-part financially distressed screens. Classification abilities and model fit are compared across the various models; the results lend support to the use of the three-screen model.

Any method used to categorize companies based on their financial condition causes two types of dependent variable measurement errors resulting from misclassifications: non-financially distressed firms categorized as financially distressed and financially distressed firms categorized as non-financially distressed. Better screening methods should reduce both errors in the dependent variable. But, without independent data indicating which companies are indeed financially distressed, it is not feasible to choose between methods. We propose to evaluate alternative screening methods based on a) the consistency of model mean square error, b) how well the variables in equation (3) categorize companies using simpler screening methods, and c) model classification accuracy as compared to results with the three-screen model.

Six different models are compared to the final early warning model of financial distress presented above in equation (3). Three of the six comparison models are based on a dependent variable derived from the three screens individually. Another three models are created when screening variables are paired together. Each of the six alternative dependent variables produces a different array of companies labeled financially distressed and non-financially distressed. The model, then, is re-estimated six additional times maintaining the original set of independent variables. F-tests and overall classification rates enable comparisons of the original model fit to the six alternative models.

Table 5 contains the results when all six models are compared to the final early warning model for financial distress. The mean square error of the final 3-screen model is as efficient as or more efficient than all six alternative models under consideration. Further, the three-screen model contains no insignificant estimated coefficients; whereas, all of the alternatives contain either one or two insignificant estimated coefficients. Including insignificant coefficients in a model may generate unreliable predictions due to the presence of larger standard errors of coefficient estimates. This concern is addressed by looking at overall model classification accuracy. Again, the three-screen model produces the highest overall classification accuracy percentage. For early warning system models, classification accuracy is one important method used to determined model fit.

Table 5
Final Early Warning Model of Financial Distress Compared:
Three-Screen Dependent Variable versus Alternative Definitions

Model	*Mean Square Error (MSE)*	*MSE Comparison to 3-Screen Model F-statistic (p-value)*	*Insignificant Coefficients?* (number)*	*Classification Accuracy(Overall)*
Final (3-screen)	.048		No	93.2%
Screen 1	.051	1.06 (.128)	Yes (2)	92.6%
Screen 2	.063	1.32 (.000)	Yes (1)	90.7%
Screen 3	.090	1.88 (.000)	Yes (2)	86.2%
Screens 1 and 2	.045	0.94 (.887)	Yes (2)	92.9%
Screens 1 and 3	.053	1.10 (.032)	Yes (1)	92.5%
Screens 2 and 3	.062	1.29 (.000)	Yes (1)	91.2%

* Excludes marginal (<.10) and statistically significant coefficients (<.05)
Screen 1: EBITDA interest coverage
Screen 2: EBIT
Screen 3: Net income before special items

The results contained in Table 5 show that models based on dependent variables derived from individual data screens have higher mean square errors, lower classification accuracy and less significant parameter estimates than with the three-screen approach. Therefore, use of a single screen is deemed inappropriate and is not discussed further.

Given that the use of individual screens is rejected, the question becomes: Are two screens sufficient, or should all three screens be used together? Two of the three paired screens, in comparison with the 3-screen model, show poorer fit based on mean square error and classification accuracy as well as fewer significant parameter estimates. Pairing Screens 1 and 2 yields about the same mean square error as the 3-screen model; however, this two-screen model has more insignificant variables and slightly lower classification accuracy. The choice of Screens 1 and 2 which has a lower mean square error rather than the 3-screen approach is rejected because it produces a model which includes insignificant variables and a slight reduction in classification accuracy. Given these results, the dependent variable based on the three-screen decision rule is the most appropriate categorization technique for defining financially distressed companies using financial statement data.

Comparing Financial Distress to Bankruptcy

Beyond the desire to develop a predictive model of financial distress is the additional objective of gaining a better understanding of the relationship between financial distress and bankruptcy. On the one hand, if financial distress and bankruptcy are part of a single on-going corporate decay process it is not unreasonable to expect identical factors to explain both. On the other hand, if the two events, financial distress and bankruptcy, are similar (in the sense of being abnormal) but different phenomenon, separate factors should explain each. A partial relationship between the processes would mean that bankruptcy starts with financial distress but only those financially distressed firms that encounter or experience other factors actually go bankrupt. Figure 1 illustrates this question by the relationship between two circles. In Panel A the two circles are concentric denoting different degrees of the same process; in Panel C the two circles do not overlap suggesting different processes. Panel B, the middle case, has some degree of similarity between the two processes. How the financial distress and bankruptcy processes compare is part of this enquiry.

To compare the two processes, the null hypothesis assumes that financial distress and bankruptcy belong to the same process, as depicted in Panel A of Figure 1. The model comparison begins with the specification in the early warning model of financial distress detailed above. This is shown in equation (4a) where $X_{1i.k}$ represents the set of factors in the financial distress model shown in equation (3).

$$\Pr(\mathrm{FD})_{\mathrm{i,j}} = a + b_1 X_{1i.j} + \varepsilon \tag{4a}$$

The specification in equation (4b) suggests the possibility of there being additional determinants of financial distress beyond those contained in $X_{1i,k}$. The additional variables considered here are those included in the Platt and Platt (1991) bankruptcy model, designated as X_{2ik}. That model was

$$\Pr(\mathrm{FD})_{\mathrm{i,j}} = a + b_1 X_{1i.j} + b_2 X_{2i,j} + \varepsilon \tag{4b}$$

chosen because it also relies on an industry-relative framework. The dependent variable in equation 4b is the probability of financial distress even though the model specification adds variables from a bankruptcy prediction model. Equation 4b tests whether the explanatory variables found in the Platt and Platt (1991) bankruptcy model also explain financial distress. If the variables are found to be predictive, then one can infer that financial distress and bankruptcy are similar processes; if not, then the two conditions are not based on the same process.

As shown in Table 6, the Platt and Platt (1991) model contains seven explanatory variables: cash flow to sales, short-term debt to total debt, net fixed assets to total assets, total debt to total assets, sales growth relative to industry output, cash flow to sales interacted with percent change in industry output and finally total debt to total assets interacted with percent change in industry output. Of these variables, one (cash flow to sales) appears in both the financial distress and the bankruptcy models. In these models, cash flow to sales was found to be inversely related to the probability of financial distress and also to the probability of bankruptcy. Although short-term debt to total debt in the bankruptcy model appears to be similar in its numerator to current portion of long term debt to total assets in the financial distress model, they are different. Short-term debt is bank debt which often can be rolled over, while current portion of long-term debt is the amount of debt that must be retired according to contractual agreements. The other variables in the bankruptcy model are different from those remaining factors in the financial distress model.

Table 6
Comparing an Industry-Relative Bankruptcy Model and an Industry-Relative Financial Distress Model

Bankruptcy Model		*Financial Distress Model*	
Variables	*Coefficient Sign*	*Variables*	*Coefficient Sign*
	Similar Variables		
Cash Flow/Sales	Negative	Cash Flow/Sales	Negative
	Dissimilar Variables		
Total Debt/Total Assets	Positive		
Net Fixed Assets/Total Assets	Positive		
Short-Term Debt/Total Debt	Positive		
Cash Flow/Sales* % Δ Industry Output	Negative		
Total Debt/Total Assets* % Δ Industry Output	Positive		
Sales Growth Relative/ % Δ Industry Output	Negative		
		EBITDA/Total Assets	Negative
		Current LTD Due/Total Assets	Positive
		Times Interest Earned	Negative
		Quick Ratio	Positive

The alternate hypotheses in equations 4a and 4b are tested using the J test (Davidson and McKinnon, 1981), which tests for significance of incremental explanatory variables beyond those contained in a given model framework. This test compares non-nested model specifications, those that do not have overlapping variables. Let X be the set of variables contained in the financial distress model and Z be the set of variables contained in the bankruptcy model, excluding cash flow to sales. Then, the null hypothesis tested is:

Ho: $Y = a + b_1 X_{1i,j} + \varepsilon$ [the bankruptcy model does not add incrementally]

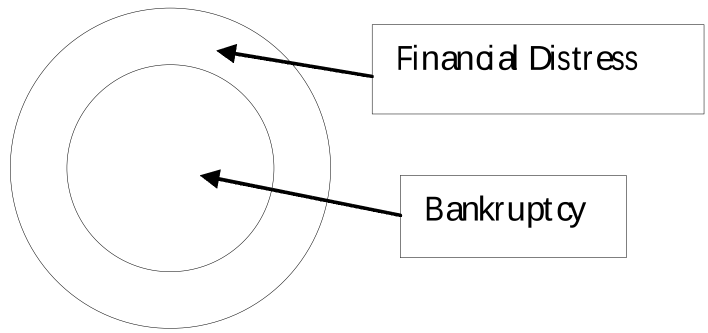
H1: $Y = a + b_1 X_{1i,j} + b_2 Z_{2i,j} + \varepsilon$ [the bankruptcy model adds incrementally]

where:

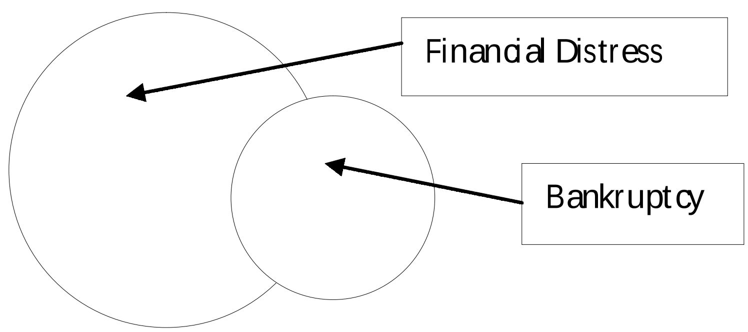
$X_{1i,j}$ = The linear combination for firm i in industry j, based on the financial distress model which includes the following variables: Cash Flow / Sales, EBITDA / TA, Current LTD Due / TA, Times Interest Earned, and Quick Ratio

Figure 1: Three Views of the Financial Distress – Bankruptcy Relationship

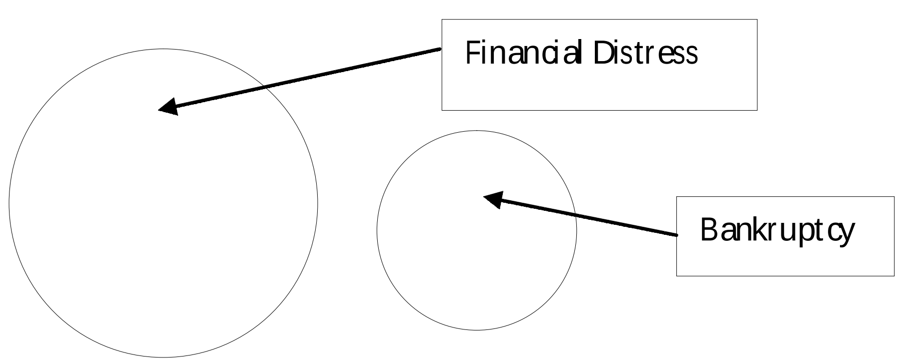
Panel A: Financial Distress and Bankruptcy are the Same Process



Panel B: Financial Distress and Bankruptcy are Similar Processes



Panel C: Financial Distress and Bankruptcy are Different Processes



$Z_{2i,j}$ = The linear combination for firm i in industry j, based on the bankruptcy model which includes the following variables: Short-Term Debt / Total Debt, Net Fixed Assets / Total Assets, Total Debt / Total Assets, Sales Growth Relative / Percent Change in Industry Output, Cash Flow / Sales Interacted with Percent Change in Industry Output and Total Debt / Total Assets Interacted with Percent Change in Industry Output

a = the estimated constant, and

b_1, b_2 = estimated parameters.

The financial distress and bankruptcy prediction models are compared using the J-test. The test evaluates the significance of the estimated parameters, b_1 and b_2. The estimated parameter, b_1 results in a value of 0.97, $p = .000$; the estimated parameter, b_2 equals .084, $p = .457$. Thus, the test results indicate that the incremental bankruptcy variables, not including cash flow to sales, do not add incrementally to those contained in the financial distress model when predicting companies in financial distress, the dependent variable. To predict financial distress, the variables in the financial distress model alone are sufficient.

Conducting the inverse analysis shows that using bankruptcy variables alone to predict financial distress are not sufficient. That is, the null hypothesis that the financial distress model does not add incrementally to the bankruptcy model is tested. The estimated parameter, b_1 is 0.245, p = .001 and the estimated parameter, b_2, is 0.815, p = .000. Thus, to predict financial distress, it is not sufficient to use bankruptcy model variables. In this case, variables contained in the financial distress model add incremental or real information to that contained in the bankruptcy model.

Understanding the Difference between Financial Distress and Bankruptcy

The set of variables explaining financial distress and those explaining bankruptcy, listed in Table 6, are dissimilar except for a single overlap variable. Inspection of those sets of variables provides a glimpse of a working model to explain the differences between financial distress and bankruptcy. The explanation is tentative because it does not lend itself to statistical verification and yet it is fairly compelling from a reasonableness perspective.

Financial distress is dependent on a set of variables that includes several from the firm's income statement including times interest earned (TIE) and an EBITDA ratio. Beyond the common variable (cash flow to sales) the bankruptcy prediction model has no further income statement variables. In many instances, income deficiencies happen to a company; they are not a direct decision. That is, a firm's products do not sell well and then its income is less than expected leading to a shortfall in both TIE and EBITDA. Firms respond to these situations in different ways and with varying degrees of success.

In contrast, the bankruptcy prediction model includes three key ratios from the firm's balance sheet. These include total debt, short-term debt, and net fixed assets ratios. The only pure debt ratio in the financial distress model is one that examines the current portion of long term debt. The balance sheet variables reveal a clear distinction between bankruptcy and financial distress: bankruptcy is related to the debt load itself while financial distress is affected by actions of the firm that violate its debt covenants causing its long term debt to accelerate and become current long term debt.[7] Violation of covenants is something that happens to a firm when their plans deviate from reality. Heavy debt loads are a corporate decision which may occur following previous instances of financial distress.

It seems then that bankruptcy is a decision that firms make when they need, for example, to protect their assets from creditors. Financial distress arises when the firm's operating decisions yield less satisfactory results. Of course, some companies file for bankruptcy protection for non-debt related reasons which is why the bankruptcy prediction model includes more than just debt ratios. It is the omission of debt ratios from the financial distress model that is so surprising. Financial distress does not arise from bad financing choices per se, but rather from a failure to execute the firm's operating plan.

Taken together, these results suggest that the bankruptcy process is not just a continuation of a downward spiraling cycle toward ultimate corporate failure. Some, indeed many companies weather the storm of financial distress and become more stable companies with more solid financial condition.

CONCLUSION

Alternate means of identifying companies in financial distress are proposed by a variety of researchers. We show that a three-screen criteria combining several previously proposed definitions yields equivalent or lower model mean square error than any one or two criteria screening models. With this categorization of companies, an industry-relative early warning model of financial distress, not bankruptcy, is built using data for 14 industries. The classification results suggest that it may be possible to take corrective actions to ameliorate financial distress before it disrupts production. Distinguishing between financially distressed and healthy companies is more difficult than the traditional comparison between bankrupt and healthy companies and hence building early warning system models to detect financial distress is more difficult.

A second inquiry compared the financial distress model to a previously estimated bankruptcy prediction model. Statistical tests reject the hypothesis that financial distress and bankruptcy are the same process. It appears that financial distress happens to companies whose operating decisions perform below expectations. Bankruptcy, in contrast, seems to be a result of a decision that companies make to relieve themselves of problems such as excess debt levels.

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NOTES

1. EBITDA covering interest expense is computed as EBITDA–interest expense.
2. Using two years is more conservative than the research methods used by Asquith *et al.* (1994) [any of 2 consecutive years]; John *et al.* (1992) [at least one year]; or Hofer (1980) [one year].
3. Two other financial distress indicators previously employed by researchers described above were not included in the screening system: Lau (1987) and Whitaker (1999). The former metric is not included because many companies do not report layoffs and thus the data are unavailable. In the

latter case, the variable is excluded because it and the EBITDA covering interest expense figure are redundant.

4. Platt and Platt (1990) argue that the industry mean should be used to normalize a financial ratio across industries. When outliers were evident in the distribution of financial ratios for an industry, the truncated mean was used in this paper.
5. All coefficients are uniformly scaled to maintain their intrinsic meaning without revealing their actual values because they remain the property of BBK, Ltd.
6. Cash flow is defined as net income plus depreciation and a mortization for a few reasons. First, this is the definition used by Platt and Platt (1991), the bankruptcy model used to compare financial distress with bankruptcy. Second, this is the definition that COMPUSTAT uses to calculate one of the cash flow items labeled “Cash Flow.” Finally, this definition measures the earnings power of the firm’s assets. Because changes in working capital accounts tend to be a transitory component of cash flow in any one year, we believe that the definition used is appropriate.
7. The current portion of long term debt also includes the regularly maturing portion of long term debt that is now due within a year.

REFERENCES

Altman, E. I., (1968), “Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy,” *Journal of Finance,* 23: 589-609.

Altman, E. and H. Izan, (1984), Identifying Corporate Distress in Australia: An Industry Relative Analysis, Working Paper, New York University.

——, G. Marco, and F. Varetto (1994), “Corporate Distress Diagnosis: Comparisons using Linear Discriminant Analysis and Neural Networks (the Italian Experience).” *Journal of Banking and Finance,* 18: 505-529.

Asquith P, R. Gertner and D. Scharfstein (1994), “Anatomy of Financial Distress: An Examination of Junk-bond Issuers,” *Quarterly Journal of Economics,* 109(3): 1189-1222.

Beaver, W. (1966), “Financial Ratios as Predictors of Failures.” *Journal of Accounting Research* 4 (Supplement): 71-102.

Brown, D. T., C. M. James, and R. M Mooradian (1992), “The Information Content of Distressed Restructurings Involving Public and Private Debt Claims,” *Journal of Financial Economics,* 33: 92-118.

Davidson, R. and J. McKinnon (1981), “Several Tests for Model Specification in the Presence of Alternative Hypotheses,” *Econometrica,* 49, 781-793.

Dixon , W. J. and F. J. Massey, Jr. (1969), *Introduction to Statistical Analysis*, 3rd edition. New York: McGraw Hill.

Frydman, H., E. I. Altman, and D. Kao (1985), “Introducing Recursive Partitioning for Financial Classification: The Case of Financial Distress,” *Journal of Finance,* 60(1): 269-291.

Gilson, S.C. (1989), “Management Turnover and Financial Distress,” *Journal of Financial Economics,* 25: 241-262.

——, K. John, and L. H. P. Lang (1990), “Troubled Debt Restructurings: An Empirical Study of Private Reorganization of Firms in Default,” *Journal of Financial Economics,* 27: 315-353.

Hausman, J., H. Ichimura, W. Newey and J. Powell (1991), “Measurement Errors in Polynomial Regression Models,” *Journal of Econometrics*, 50: 271-295.

Hofer, C. W. (1980), "Turnaround Strategies," *Journal of Business Strategy*, Summer: 19-31.

Hill, N. T., S. E. Perry, and S. Andes (1996), "Evaluating Firms in Financial Distress: An Event History Analysis," *Journal of Applied Business Research,* 12(3): 60-71.

John, K, L. H. D. Lang and J. Netter (1992), "The Voluntary Restructuring of Large Firms in Response to Performance Decline," *Journal of Finance,* 47: 891-917.

Lachenbruch, P. (1967), "An Almost Unbiased Method of Obtaining Confidence Intervals for the Probability of Misclassification in Discriminant Analysis," *Biometrics,* 23, 639-645.

Lau, A. H. (1987), "A Five-State Financial Distress Prediction Model," *Journal of Accounting Research,* 25(1): 127-138.

Lev, B. (1969), Industry Averages as Targets for Financial Ratios, *Journal of Accounting Research*, 7, 290-299.

Lin, P., L. Ko, and E. Blocher (1999), "Prediction of Corporate Financial Distress: An Application of the Composite Rule Induction System," paper presented at the 1999 Annual Meetings of the American Accounting Association, San Diego.

Lo, A. (1986), "Logit versus Discriminant Analysis: A Specification Test and Application to Corporate Bankrtupcy," *Journal of Econometrics,* 31: 151-178.

Mensah, Y. M. (1984), "An Examination of the Stationarity of Multivariate Bankruptcy Prediction Models: A Methodological Study," *Journal of Accounting Research,* 22: 380-395.

Platt, H. and M. B. Platt (1991a), "A Note on the Use of Industry-Relative Ratios in Bankruptcy Prediction," *Journal of Banking and Finance,* 15: 1183-1194.

——(1992), "Credit Risk and Yield Differentials for High Yield Bonds," *Quarterly Journal of Business and Economics,* 31(3): 51-68.

——(2002), "Predicting Corporate Financial Distress: Reflections on Choice-Based Sample Bias," *Journal of Economics and Finance,* 26(2): 184-199.

——and J. G. Pedersen (1994),"Bankruptcy Prediction with Real Variables." *Journal of Business Finance & Accounting,* 21(4): 491-510.

Queen, M. and R. Roll (1987), "Firm Mortality: Using Market Indicators to Predict Survival." *Financial Analysts Journal,* May-June: 9-26.

Schipper, K. (1977), "Financial Distress in Private Colleges." *Journal of Accounting Research,* 15 (Supplement): 1-40.

Thedodossious, P, E. Kayha, R. Saidi, and G. Philippatos (1996), "Financial Distress and Corporate Acquisitions: Further Empirical Evidence." *Journal of Business Finance and Accounting,* 23 (5&6): 699-719.

Whitaker, R. B. (1999), "The Early Stages of Financial Distress." *Journal of Economics and Finance*, 23(2): 123-133.

Yang, A. R., M. B. Platt and H. D. Platt (1999), "Probabilistic Neural Networks in Bankruptcy Prediction," *Journal of Business Research,* 44(2): 67-74.

Zmijewski, M. E. (1984), "Methodological Issues Related to the Estimation of Financial Distress Prediction Models," *Journal of Accounting Research,* 22 (Supplement): 59-82.