Applying Bankruptcy Prediction Models to Distressed High Yield Bond Issues

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Over the past 20 years an intriguing phenomenon in the financial markets has been the rise and fall and second rise of high-yield bonds. Informed investors are fully aware that there is a clear danger of default on these assets. Yet, despite the real possibility of loss of both principal and interest, billions of dollars have flowed into these securities. Today's investor in this market is more than the sophisticated institutional investor such as a foundation, endowment, or defined-benefit pension system; small investors are also choosing high-yield bond mutual funds to participate in this unique market.

Given that modern financial theory generally accepts that rational investors seek a risk and return trade-off that is appropriate for their investment objectives, it is reasonable to assume that many investors—both private and institutional—find these high-yield debt securities to have characteristics that complement assets in a diversified portfolio and enhance its risk and return features. This is an asset class with a legitimate place in many portfolios.

Yet how does the portfolio manager—individual or institutional—determine which particular high-yield bonds are likely to default and should be excluded? Given that these assets have already been declared by the debt rating agencies to have a substantial probability of default, is there a mechanism beyond the rating itself for the investor to differentiate the high-yield asset that will survive and the one that will fail?

I. DEFAULT AND BANKRUPTCY LITERATURE

Studies on high-yield debt default have produced interesting results. For example, Altman [1989] and Asquith, Mullins, and Wolff [1989] have found that the longer a high-yield bond is outstanding, the greater the likelihood of default. Lehman and Fridson [1995] have determined that high-yield debt with high coupon payments is more likely to default than similarly rated low-coupon debt.

Alessandrini [1999] explores the relationship between high-yield default and the business cycle, and other authors have examined the impact of a number of other variables. Yet the literature still does not provide a complete and definitive model for explaining default on high-yield instruments.

Huffman and Ward [1996] have offered a methodology for the prediction of default for high-yield bonds at time of issue. They review the bankruptcy literature initiated by Altman, and collect most of the variables used in the many subsequent studies. Then, using a multivariate logistic regression analysis, they attempt to ascertain the variables that would allow them to predict default at time of issue.

Their conclusion is very different from those of other studies, which has been that default is a function of a firm's high growth rate in assets and working capital, coupled with a lower profit margin. While this is clearly a contribution, the authors do not produce a complete and definitive model for explaining default on these securities.

There is plenty of research that attempts to predict the bankruptcy of a firm. While bankruptcy and default on a debt instrument are technically not the same event, they represent different phases of financial distress, so the literature on bankruptcy models is worth exploring in the search for a methodology to predict high-yield bond defaults.

Bankruptcy prediction modeling has its key foundations in the work of Altman [1968]. Altman relies on multiple discriminant analysis to develop a bankruptcy prediction methodology. He uses key accounting ratios that together produce a Z-score that indicates if a firm would fail. Altman reports a high predictive power for his model.

Altman's research on using accounting ratios to predict bankruptcy stimulated a great deal of interest among researchers. Boritz [1991] asserts that in the next 20 years researchers used over 65 different accounting ratios in a wide variety of methodologies attempting to predict corporate bankruptcy. Some of the more frequently cited research on using accounting ratios to predict bankruptcy includes Beaver [1968], Altman, Haldeman, and Narayanan [1977], Collins [1980], Ohlson [1980], and Platt and Platt [1991].

Nearly two decades after Altman's initial foray into the field of bankruptcy prediction, a new approach began to emerge. Altman had relied on accounting ratios, following the standard accounting approach of observing critical relationships between equity and debt, current assets and liabilities, and other key variables. The new approach was based instead entirely on cash flows. This approach has an intuitive logic to it, as a firm that has insufficient cash to pay its debts is frequently subject to corporate bankruptcy.

Gentry, Newbold, and Whitford [1985a, 1985b] were among the first to develop such an approach. Their work was soon followed by an additional cash flow study presented by Aziz, Emanuel, and Lawson [1989]. Although the methodologies in these two studies are somewhat different, they share a common finding of a significant difference in cash flows between bankrupt and non-bankrupt firms.

II. OBJECTIVE

We want to see whether well-known methodologies for predicting corporate bankruptcy can also be used to predict default on high-yield bonds. To explore this question, we apply the approaches in four of the major bankruptcy prediction studies to predicting default on high-yield bonds at one, two, and three years before default. We use two accounting ratio methodologies as developed by Altman [1968] and Ohlson [1980], and two cash flow techniques as developed by Gentry, Newbold, and Whitford [1985a] and Aziz, Emanuel, and Lawson [1988].

While Huffman and Ward [1996] use some of the variables from these studies in their research, they examine separately only the original Altman [1968] model. We develop a new approach to help identify variables that could explain the default of high-yield bonds. We also extend the work of Huffman and Ward [1996] by reexamining Altman with a different data set, and by also examining the three other major studies.

III. DATA

We use the Chase High-Yield Database, which includes a large portion of the high-risk issues, to identify all new public high-yield debt issued in the years 1997–2000 and defaulted in the years 1997–2002. Financial data on each firm are collected from the Compustat database. Foreign and privately held firms not appearing in Compustat are not included in the data sample.

The final data sample consists of 104 high-yield bonds. Of these bonds, 44 would ultimately be in default by March 2002, and the remaining 60 bonds were to remain viable assets.

Exhibit 1 shows that the 104 bonds represent 19 different industries and include a diverse mix of industries for both defaulting and non-defaulting bonds. Our data sample is similar in size to the Huffman and Ward [1996] sample. Their data set consists of 171 issues, of which 54 were defaulted bonds.

It is worth noting that 5 of the 44 defaulting high-yield bonds in our data set would be in default within less than one year from issue, one of them within six months of issue. Only 7 of the 44 high-yield bonds took over three years to default. That corporations could sell debt that defaults so quickly after issue surely indicates some deficiency in the assessment techniques of analysts and portfolio managers.

IV. FOUR BANKRUPTCY MODELS

Our four models represent two very different approaches to the problem of predicting bankruptcy. The first two rely on accounting ratios to make predictions,

EXHIBIT 1
Data Set by Industry

Industry	Defaulting Bonds	Non-Defaulting Bonds
Aerospace	2	4
Chemicals	2	2
Consumer Non-Durables	8	8
Energy	1	3
Financial	3	3
Food and Drugs	1	1
Food/Tobacco	3	3
Forest Products/Containers	0	2
Gaming/Leisure	1	3
Healthcare	1	3
Housing	3	1
Information Technology	2	2
Manufacturing	1	2
Media/Entertainment	12	10
Metals/Minerals	1	2
Retail	1	1
Service	1	6
Transportation	0	2
Utility	1	2
Total	44	60

and the other two are based on cash flows.

Altman [1968] uses multiple discriminant analysis to develop a model with five accounting ratio variables that could be used to predict corporate bankruptcy:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5 \tag{1}$$

where

X_1 = working capital/total assets;
X_2 = retained earnings/total assets;
X_3 = earnings before interest and taxes/total assets;
X_4 = market value of equity/book value of total debt;
X_5 = sales/total assets; and
Z = overall index.

Altman's analysis produces a Z-score for each company that indicates if the firm would enter bankruptcy. Working with a group of bankrupt companies and a group of non-bankrupt companies, Altman reports his technique was accurate in predicting bankruptcy or non-bankruptcy in 95% of cases during the year after the issue of financial statements. The technique was accurate 72% of the time to predict bankruptcy or non-bankruptcy in the two years that followed the issue of statements. The predictive financial power diminished to 48%, 29%, and 36% for predictions three, four, and five years out.

Ohlson [1980] also uses accounting ratios, but introduces *probabilistic estimates of failure* in a conditional logit model:

$$l(B) = \sum_{i \in S_1} \log P(X_i, B) + \sum_{i \in S_2} \log[1 - P(X_i B)] \tag{2}$$

where

B = vector of unknown parameters;
S_1 = index set of bankrupt firms;
P = some probability function, $0 \leq P \leq 1$;
X_i = vector of predictors for the i-th observation;
$P(X_i, B)$ = probability of bankruptcy for any given X_i and B; and
S_2 = index set of non-bankrupt firms.

Ohlson's approach uses nine variables to predict bankruptcy in corporations:

SIZE = log(total assets/GNP);
TLTA = total liabilities/total assets;
WCTA = working capital/total assets;
CLCA = current liabilities/current assets;
OENEG = one if total liabilities are greater than total assets, and zero otherwise;
NITA = net income/total assets;
FUTL = funds provided by operations/total liabilities:
INTWO = one if net income was negative for the last two years, and zero otherwise; and
CHIN = $(NI_t - NI_{t-1})/(|NI_t| + |NI_{t-1}|)$, where NI_t is net income in the most recent period.

Working with a group of bankrupt and non-bankrupt firms, Ohlson uses his approach to predict bankruptcy. For one, two, and three years before the bankruptcy event, he reports correct predictions of 96.12%, 95.55%, and 92.84%. Ohlson emphasizes his use of data from 10-K filings; most studies prior to his (including Altman's) had used data from the *Moody's Manuals*.

Gentry, Newbold, and Whitford [1985a] were the first to use cash flows to predict bankruptcy. Their methodology has its origins in Herfert's cash flow model [1982]. The Gentry, Newbold, and Whitford (GNW) methodology uses eight cash flow variables to predict a firm's entering into bankruptcy:

$$\text{NOFF} + \text{NWCFF} + \text{NFFF} + \text{FCE} + \text{NIFF} + \text{DIV} + \text{NOTHER} - \text{CC} = 0 \tag{3}$$

where

NOFF = net operating inflows;
NWCFF = net working capital;
NFFF = net financing flow (i.e., change in total debt and common stock);
FCE = fixed coverage expense;
NIFF = net capital expenditures;
DIV = dividends;
NOTHER = net other asset and liability flows; and
CC = net change in cash and marketable securities.

Analysis of the GNW data sample shows differences in the mean values of cash flows and their standard deviations in comparisons of bankrupt and non-bankrupt firms. A logit model is used to generate coefficients for the variables, and GNW use these values to predict the failure or non-failure of the firms in their data set. 79% of failed firms are classified correctly using data one or three years prior to failure. For the firms predicted to remain healthy, 88% remained healthy (non-bankrupt) one year from the forecast, and 79% of them were still non-bankrupt three years later.

Aziz, Emanuel, and Lawson [1988] develop an analysis similar to the cash flow approach in GNW. The Aziz, Emanuel, and Lawson (AEL) approach relies on six key cash flow variables to predict a firm's entering into bankruptcy. The identity is stated as:

$$(k_j - h_j) - (A_j + R_j - Y_j) - H_j - t_j - (F_j - N_j - M_j) + (D_j - B_j) \tag{4}$$

where

k_j = cash collected from customers in year j;
h_j = operating cash outflow;
A_j = replacement investment;
R_j = growth investment;
Y_j = proceeds from assets displaced in year j;
H_j = change in liquidity in year j;
t_j = taxes paid in year j;
F_j = interest payments in year j;
N_j = medium- or long-term debt raised or retired in year j;
M_j = short-term debt raised or retired in year j;
D_j = dividends paid in year j; and
B_j = equity capital raised or repaid in year j.

To ascertain the suitability of the model, AEL use both multiple discriminant analysis and logistic regression (reporting the logit results) to examine the use of these variables in the model with data one, two, three, four, and five years prior to bankruptcy. The technique varies in predictive power (considering both bankrupt and non-bankrupt firms) from 91.8% one year out to a low of 78.6% in year three.

V. BANKRUPTCY METHODOLOGIES AND HIGH-YIELD BONDS

We apply all four bankruptcy methodologies to our high-yield data set. The data for each firm are analyzed using the firm's financial data one year, two years, and three years before default. Mixed but unimpressive results are obtained, indicating the approaches are all significantly less successful in predicting default of high-yield bonds than they are in predicting bankruptcy.

The results are reported in Exhibit 2. No technique is acceptable at predicting default among the bonds in the data set.

The overall accuracy rate of the Altman methodology is only 37.5% one year before default, 36.4% two years before default, and 39.3% three years before default. Given that the Altman methodology never produces better than a 39% accuracy rate in predicting default, it must be rejected as a predictor of high-yield bond defaults.

The Ohlson approach produces similar results. Its overall accuracy rate is 49% one year before default and 43.4% two years before default, dropping to 46.1% three years before default. Like the Altman approach, the Ohlson method never produces an accuracy rate in predicting default that even equals that of a coin toss. It must also be rejected as a predictor of high-yield bond defaults.

We are not surprised to see that the two cash flow models actually fare better than the accounting ratio models as predictors of high-yield default. The GNW approach produces the most impressive results of the four

EXHIBIT 2

Accuracy of Predictions for Bankruptcy Methodologies

	One year prior to default				Two years prior to default				Three years prior to default			
	Number	% Correct	% Incorrect	% in Zone of Ignorance	Number	% Correct	% Incorrect	% in Zone of Ignorance	Number	% Correct	% Incorrect	% in Zone of Ignorance
Altman*												
Defaulting	44	84.1	9.1	6.8	42	83.3	14.3	2.4	37	94.6	5.4	0.0
Non-defaulting	60	3.3	85.0	11.7	57	1.8	91.2	7.0	52	0.0	90.4	9.6
Total	104	37.5	52.9	9.6	99	36.4	53.5	10.1	89	39.3	55.1	5.6
Ohlson												
Defaulting	44	100.0	0.0		42	95.2	4.8		37	100.0	0.0	
Non-defaulting	60	11.7	88.3		57	5.3	94.7		52	7.7	92.3	
Total	104	49.0	51.0		99	43.4	56.6		89	46.1	53.9	
GNW												
Defaulting	44	45.5	54.5		42	71.4	28.6		37	73.0	27.0	
Non-defaulting	60	73.3	26.7		57	52.6	47.7		52	15.4	84.6	
Total	104	61.5	38.5		99	60.6	39.4		89	39.3	60.7	
AEL												
Defaulting	44	79.5	20.5		42	64.3	35.7		37	70.3	29.7	
Non-defaulting	60	31.7	68.3		57	38.6	61.4		52	44.2	55.8	
Total	104	51.9	48.1		99	49.5	50.5		89	55.1	44.9	

* *The percentages for the Altman approach would not add up to 100% without the extra column, because some Z-scores place certain issues within what Altman calls a "zone of ignorance," where predictions could not be made.*

models. The GNW accuracy rate is 61.5% one year before default, rising to 60.6% two years before default, and then surprisingly to 39.3% three years before default. The AEL methodology produces accuracy rates of 51.9%, 49.5% and 55.1%, at one, two, and three years, before default. The low accuracy rates of these techniques clearly do not qualify them as acceptable mechanisms for the prediction of high-yield default.

We wondered if there might be macroeconomic factors—separate from security risks—associated with the bond issues and the period of time, and if so, this problem could distort the results of our analysis in some way. While the creators of the four methodologies do not raise this issue as a concern in the prediction of bankruptcy, it could still be a factor here.

To address this issue, we regroup the bonds into data subsets based on year of issuance. Each model is then reapplied to the data subsets to see if empirical results could be any different. The result of this analysis is consistent with the original analysis of the full data set, leading us to conclude that there is no time-dependence issue in the failure of the four methodologies to predict defaults.

VI. NEW METHODOLOGY

We use a multivariate logistic regression analysis to examine 24 ratios and variables to predict future default on high-yield bonds. The variables and ratios are reported in Exhibit 3. The model is expressed as:

$$l(B) = \sum_{i \in S_1} \log P(X_i, B) + \sum_{i \in S_2} \log\left[1 - P(X_i B)\right] \qquad (5)$$

where the variables are as defined before.

Our approach uses six variables to predict default in high-yield bonds:

LOGTA = log of total assets;
TETA = total equity/total assets;
EBITSALES = EBIT/sales;
CFOSALES = operating cash flow/sales;
CFOTA = operating cash flow/total assets; and
EBITINTEX = EBIT/interest expense.

Our model specifications are

EXHIBIT 3

Variables Tested in Logistic Regression Model

LOGTA	Log of Total assets
TETA	Total Equity / Total Assets
EBITSALES	EBIT / Sales
EBITDASALES	EBITDA / Sales
NIAFTEREXSALES	Net Income after Extraordinary Items / Sales
NPFLAG	Net Income positive prior year = 1
ROA	Return on Assets
ROCE	Return on Common Equity
ROE	Return on Equity
TACE	Total Assets / Common Equity
CASHSALES	Cash / Sales
CELTD	Common Equity / Long-Term Debt
TDTA	Total Debt / Total Assets
RETA	Retained Earnings / Total Assets
CDCE	Current Debt / Common Equity
EBITTA	EBIT / Total Assets
CFOTD	CFO / Total Debt
EBITDATA	EBITDA / Total Assets
CFOSALES	CFO / Sales
CFOTE	CFO / Total Equity
CFOINTEXP	CFO / Interest Expense
CFOTA	CFO / Total Assets
EBITINTEX	EBIT / Interest Expense
CFOINTTDTE	CFO plus Interest Expense / Total Debt + Total Equity

$$\begin{aligned} l(B) = 3.65 - 1.04\ \text{LOGTA} - 3.67\ \text{TETA} + \\ 4.57\ \text{EBITSALES} - 22.05\ \text{CFOSALES} - \\ 4.39\ \text{CFOTA} + 0.11\ \text{EBITINTEX} \end{aligned} \qquad (6)$$

All variables but operating cash flow/total assets are found to be significant at the 5% level. CFOTA is significant at the 10% level. SAS analysis of the logistic procedure reports the procedure to be 90% consistent with the association of predicted probabilities and observed responses.

Note that the variables in Equation (6) fall into three groups: a size measure, two efficiency ratios, and three cash flow relationships. Like Ohlson [1980], we find the size of the firm to be significant. Considering the variables in the bankruptcy studies, it should come as no surprise that efficiency of operations and cash flows would also be important.

We apply the model at one, two, and three years prior to default to attempt to make default predictions. The results are reported in Exhibit 4.

The predictive results of this methodology prove to be significantly better than when we use the four bankruptcy models. One year prior to default, we could correctly classify 79.6% of the bonds into defaulting and non-defaulting groups. For two and three years prior to default, the accuracy rate of the model drops to 72.6% and 68.2%.

With this model, we obtain much better predictions than with any of the individual bankruptcy models or their general approaches (i.e., key accounting ratios or cash flows). The predictive power of this model also exceeds the predictive power that Huffman and Ward [1996] report for their methodology.

VII. CONCLUSIONS

The four bankruptcy prediction studies we use in our analysis all have claimed the ability to predict bankruptcy with a high degree of accuracy within one to three years prior to the default event. When we apply the same four approaches to the prediction of default on high-yield bonds, all four fail—none of them has better than a 61.5% accuracy rate in any period—and that particular model only had a 39% accuracy at three years before default.

Clearly, the established bankruptcy approaches do not work for high-yield bonds, and further study is necessary to develop an analytical technique that can predict these defaults.

We can draw two conclusions from the inability of the four bankruptcy prediction approaches to predict high-yield debt default. The first and most logical explanation is simply that the data sample is entirely made up of high-yield bonds, which implies that these are firms with generally poor accounting ratios and cash flows. It is not unexpected that the models and variables researchers have used to predict bankruptcy would draw primarily a negative conclusion about these companies and their associated debt. These are high-yield bonds for a reason.

Second, there is no assurance that the same variables will always work in these models, regardless of the data set or time period from which a sample is drawn. It may be that the models need to be reworked, given that over 35 years have passed since Altman's 1968 study.

We believe the better results from our default prediction model lie in the use of a variety of variables, rather than an analysis that relies exclusively on simple cash flows or accounting ratios. (For example, Moeller and Molina [2003] conclude that time-sensitive variables might be needed to develop more accurate prediction models.)

Recent scandals in American business have surely driven home the point that balance sheet and income statement items can be and have been severely manipulated. Anyone who is familiar with the implosions of Enron and WorldCom can understand a suspicion of

EXHIBIT 4

Accuracy of Predictions for New Methodology

	One year prior to default	Two years prior to default	Three years prior to default
Number of issues	103	96	85
Percent correctly classified	79.6	72.6	68.2

accounting ratios as adequate to predict the health of a firm issuing junk bonds.

We know that cash flows are much more difficult than accounting ratios to manipulate. Of the methodologies examined in this study, we do note that the cash flow approaches of Gentry, Newbold, and Whitford and Aziz, Emanuel, and Lawson produce better predictions than the accounting ratio methodologies. Yet, cash flows only clearly do not explain these defaults.

We believe that the integration of cash flow measures and accounting efficiency ratios points us in the right direction for predicting default of high-yield debt.

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