CORPORATE DISTRESS PREDICTION MODELS IN A TURBULENT ECONOMIC AND BASEL II ENVIRONMENT

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Corporate Distress Prediction Models in a Turbulent Economic and Basel II Environment

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This paper discusses two of the primary motivating influences on the recent development/revisions of credit scoring models, - the important implications of Basel II's proposed capital requirements on credit assets and the enormous amounts and rates of defaults and bankruptcies in the United States in 2001-2002. Two of the more prominent credit scoring techniques, our Z-Score and KMV's EDF models, are reviewed. Both models are assessed with respect to default probabilities in general and in particular to the infamous Enron and WorldCom debacles in particular. In order to be effective, these and other credit risk models should be utilized by firms with a sincere credit risk culture, observant of the fact that they are best used as an additional tool, not the sole decision making criteria, in the credit and security analyst process.

Key Words: Credit Risk Models, Default Probabilities, Basel II, Z-Score, KMV

1. Introduction

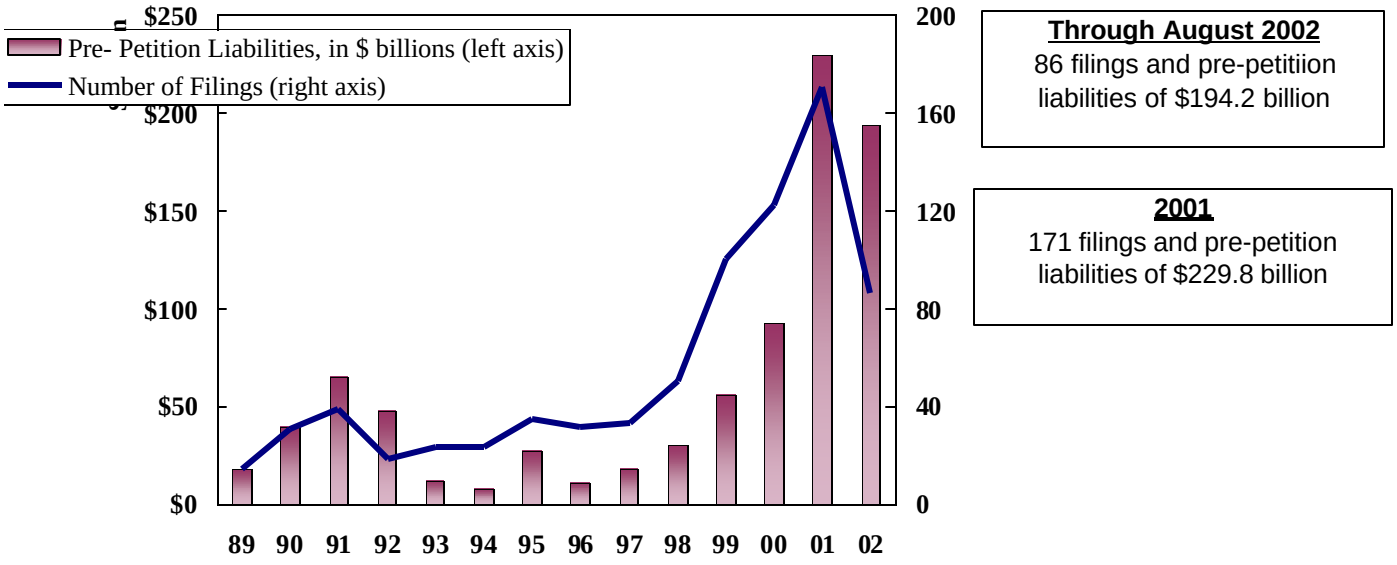
Around the turn of the new century, credit scoring models have been remotivated and given unprecedented significance by the stunning pronouncements of the new Basel Accord on credit risk capital adequacy - - the so-called Basel II (see Basel [1999] and [2001]). Banks, in particular, and most financial institutions worldwide, have either recently developed or modified existing internal credit risk systems or are currently developing methods to conform with best practice systems and processes for assessing the probability of default (PD) and, possibly, loss-given-default (LGD) on credit assets of all types. Coincidentally, defaults and bankruptcies reached unprecedented levels in the United States in 2001 and have continued at even higher levels in 2002. Indeed,

companies that filed for bankruptcy/reorganization under Chapter 11 with greater than $100 million liabilities reached at least $240 billion in liabilities in 2001, even with Enron's understatement at the time of filing (see Figure 1). And there were 39 firms in 2001 that filed for protection under the US bankruptcy code with liabilities greater than $1 billion! The pace of these large bankruptcies has continued in 2002 with another 25 firms of such great size filing in the first eight months. In the public bond arena, over $63 billion of U.S. domestic public, high yield (below investment grade) bonds defaulted in 2001 and the default rate was almost a record 9.8% (dollar weighted). In addition, in only the first eight months of 2002, the corporate high yield bond default rate rose above 12.0%, powered by 258 defaulting issues from 69 companies, including the largest default in history, WorldCom.[1]

[1] Data is derived from the NYU Salomon Center corporate bond default and bankruptcy databases.

FIGURE 1

TOTAL LIABILITIES OF PUBLIC COMPANIES FILING FOR CHAPTER 11 PROTECTION 1989-2002 YTD*



Note: 8/31/2002 only. Minimum $100 million in liabilities
Source: NYU Salomon Center Bankrupcty Filings Database

This paper discusses a model developed by the author over 30 years ago, the Z-Score model, and its relevance to these recent developments. In doing so, we will provide some updated material on the Z-Score model's tests and applications over time as well as two modifications for greater applicability. We also discuss another widely used credit risk model, known as the KMV approach, and compare both KMV and Z-Score in the now infamous Enron (2001) and WorldCom bankruptcy debacles. The paper is not meant to be a comparison of all of the well known and readily available credit scoring models, such as *Moody's RiskCalc®, CreditSight's BondScore®*, the *Kamakura* approach, or the *ZETA®* scoring model. Finally, we summarize a recent report (Altman, Brady, Resti and Sironi, [2002]) on the association between aggregate PD and recovery rates on defaulted credit assets.

A major theme of this paper is that the assignment of appropriate default probabilities on corporate credit assets is a three-step process involving the sequential use of:

(1) credit scoring models,

(2) capital market risk equivalents - - usually bond ratings, and

(3) assignment of PD and possibly LGDs on the credit portfolio.[2]

Our emphasis will be on step (1) and how the Z-Score model, (Altman, 1968), has become the prototype model for one of the three primary structures for determining PDs. The other two credit scoring structures involve either the bond rating process itself or option pricing capital market valuation techniques, typified by the KMV expected default

[2] Some might argue that a statistical methodology can combine steps (1) and (2) where the output from (1) automatically provides estimates of PD. This is one of the reasons that many "modelers" of late and major consulting firms prefer the logit-regression approach, rather than the discriminant model that this author prefers.

frequency (EDF) approach, (McQuown [1993], Kealhofer [2000], and KMV [2000]). These techniques are also the backbone of most credit asset value-at-risk (VaR) models. In essence, we feel strongly that if the initial credit scoring model is sound and based on comprehensive and representative data, then the credit VaR model has a chance to be accurate and helpful for both regulatory and economic capital assignment and, of course, for distress prediction. If it is not, no amount of quantitative sophistication or portfolio analytic structures can achieve valid credit risk results.

2. Credit Scoring Models

Almost all of the statistical credit scoring models that are in use today are variations on a similar theme. They involve the combination of a set of quantifiable financial indicators of firm performance with, perhaps, a small number of additional variables that attempt to capture some qualitative elements of the credit process. Although, this paper will concentrate on the quantitative measures, mainly financial ratios and capital market values, one should not underestimate the importance of qualitative measures in the process.[3] Starting in the 1980's, some practitioners, and certainly many academicians, had been moving toward the possible elimination of ratio analysis as an analytical technique in assessing firm performance. Theorists have downgraded arbitrary rules of thumb (such as company ratio comparisons) that are widely used by practitioners. Since attacks on the relevance of ratio analysis emanate from many esteemed members of the scholarly world, does this mean that ratio analysis is limited to the world of "nuts and bolts?" Or, has the significance of such an approach

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[3] Banking practitioners have reported that these so-called qualitative elements, that involve judgment on the part of the risk officer, can provide as much as 30-50% of the explanatory power of the scoring model.

been unattractively garbed and therefore unfairly handicapped? Can we bridge the gap, rather than sever the link, between traditional ratio analysis and the more rigorous statistical techniques that have become popular among academicians?

3. Traditional Ratio Analysis

The detection of company operating and financial difficulties is a subject which has been particularly amenable to analysis with financial ratios. Prior to the development of quantitative measures of company performance, agencies had been established to supply a qualitative type of information assessing the creditworthiness of particular merchants. (For instance, the forerunner of Dun & Bradstreet, Inc. was organized in 1849 in order to provide independent credit investigations).

Classic works in the area of ratio analysis and bankruptcy classification were performed by Beaver (1967, 1968). His univariate analysis of a number of bankruptcy predictors set the stage for the multivariate attempts, by this author and others, which followed. Beaver found that a number of indicators could discriminate between matched samples of failed and nonfailed firms for as long as five years prior to failure. However, he questioned the use of multivariate analysis. The Z-Score model, developed by this author at the same time (and published in 1968), that Beaver was working on his own thesis, did just that - constructed a multivariate model.

The aforementioned studies imply a definite potential of ratios as predictors of bankruptcy. In general, ratios measuring profitability, liquidity, leverage, and solvency seemed to prevail as the most significant indicators. The order of their importance is not clear since almost every study cited a different ratio as being the most effective indicator of impending problems. An appropriate extension of the previously cited studies,

therefore, was to build upon their findings and to combine several measures into a meaningful predictive model. However, several questions remained:

(1) which ratios are most important in detecting credit risk problems?

(2) what weights should be attached to those selected ratios?

(3) how should the weights be objectively established?

4. Discriminant Analysis

After careful consideration of the nature of the problem and of the purpose of this analysis, we chose multiple discriminant analysis (MDA) in our original constructions, as the appropriate statistical technique. Although not as popular as regression analysis, MDA had been utilized in a variety of disciplines since its first application in the biological sciences in 1930's. MDA is a statistical technique used to classify an observation into one of several a *priori* groupings dependent upon the observation's individual characteristics. It is used primarily to classify/or make predictions in problems where the dependent variable appears in qualitative from, for example, male or female, bankrupt or nonbankrupt. Therefore, the first step is to establish explicit group classifications. The number of original groups can be two or more. After the groups are established, data are collected for the objects in the groups. MDA in its most simple form attempts to derive a linear combination of these characteristics that "best" discriminates between the groups. The technique has the advantage of considering an entire profile of characteristics common to the relevant firms, as well as the interaction of these properties.

5. Development of the Z-Score Model

Sample Selection

The initial sample was composed of 66 corporations with 33 firms in each of the two groups: bankrupt and non-bankrupt. The bankrupt (distressed) group were all manufacturers that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act from 1946 through 1965. A 20-year sample period is not the best choice since average ratios do shift over time. Ideally, we would prefer to examine a list of ratios in time period t in order to make predictions about other firms in the following period (t+1). Unfortunately, because of data limitations at that time, it was not possible to do this. Recent "heavy" activity of bankruptcies now presents a more fertile environment. Recognizing that this group is not completely homogeneous (due to industry and size differences), we made a careful selection of nonbankrupt (nondistressed) firms. This group consists of a paired sample of manufacturing firms chosen on a stratified random basis. The firms are stratified by industry and by size, with the asset size range between $1 and $25 million. Yes, in those days $25 million was considered a very large bankruptcy! The data collected were from the same years as those compiled for the bankrupt firms. For the initial sample test, the data are derived from financial statements that are dated one annual reporting period prior to bankruptcy. Some analysts, e.g., Shumway (2002), have criticized this "static" type of analysis, but we have found that the one-financial-statement-prior-to-distress structure yields the most accurate post-model building test results.

Variable Selection and Weightings

After the initial groups were defined and firms selected, balance sheet and income statement data were collected. Because of the large number of variables that are potentially significant indicators of corporate problems, a list of 22 potentially helpful variables (ratios) were compiled for evaluation. From the original list, five were selected as doing the best overall job together in the prediction of corporate bankruptcy. The contribution of the entire profile is evaluated and, since this process is essentially iterative, there is no claim regarding the optimality of the resulting discriminant function.

The final discriminant function is given in Figure 2. Note that the model does not contain a constant term.[4] One of the most frequently asked questions is: "How did you determine the coefficients or weights?" These weights are objectively determined by the computer algorithm and not by the analyst. As such, they will be different if the sample changes or if new variables are utilized.

Figure 2
The Z-Score Model

$$Z = 1.2\,X_1 + 1.4\,X_2 + 3.3\,X_3 + 0.6\,X_4 + 1.0\,X_5$$

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 equity/book value of total liabilities,
X_5 = sales/total assets, and
Z = overall Index or Score

Source: Altman (1968)

[4] This is due to the particular software utilized and, as a result, the relevant cutoff score between the two groups is not zero. Many statistical software programs now have a constant term, which standardizes the cutoff score at zero if the sample sizes of the two groups are equal.

X_1, Working Capital/Total Asset (WC/TA)

The working capital/total assets ratio is a measure of the net liquid assets of the firm relative to the total capitalization. Working capital is defined as the difference between current assets and current liabilities. Liquidity and size characteristics are explicitly considered. This ratio was the least important contributor to discrimination between the two groups. In all cases, tangible assets, not including intangibles, are used.

X_2, Retained Earnings/Total Assets (RE/TA)

Retained earnings (RE) is the total amount of reinvested earnings and/or losses of a firm over its entire life. The account is also referred to as earned surplus. This is a measure of cumulative profitability over time. The age of a firm is implicitly considered in this ratio. It is likely that a bias would be created by a substantial reorganization or stock dividend and appropriate readjustments should, in the event of this happening, be made to the accounts.

In addition, the RE/TA ratio measures the leverage of a firm. Those firms with high RE relative to TA have financed their assets through retention of profits and have not utilized as much debt. This ratio highlights either the use of internally generated funds for growth (low risk capital) vs. OPM (other people's money) - higher risk capital.

X_3, Earnings Before Interest and Taxes/Total Assets (EBIT/TA)

This is a measure of the productivity of the firm's assets, independent of any tax or leverage factors. Since a firm's ultimate existence is based on the earning power of its assets, this ratio appears to be particularly appropriate for studies dealing with credit risk.

X_4, Market Value of Equity/Book Value of Total Liabilities (MVE/TL)

Equity is measured by the combined market value of all shares of stock, preferred and common, while liabilities include both current and long term. The measure shows how much the firm's assets can decline in value (measured by market value of equity plus debt) before the liabilities exceed the assets and the firm becomes insolvent. We discussed this "comparison" long before the advent of the KMV approach (which I will discuss shortly) - that is, before Merton [1974] put these relationships into an option-theoretic approach to value corporate risky debt. KMV used Merton's work to springboard into its now commonly used credit risk measure - the Expected Default Frequency (EDF).

This ratio adds a market value dimension that most other failure studies did not consider. At a later point, we will substitute the book value of net worth for the market value in order to derive a discriminant function for privately held firms (Z') and for non-manufacturers (Z").

X_5, Sales/Total Assets (S/TA)

The capital-turnover ratio is a standard financial ratio illustrating the sales generating ability of the firm's assets. Net sales is used. It is a measure of management's capacity to deal with competitive conditions. This final ratio is unique because it is the least significant ratio and, on a univariate statistical significance test basis, it would not have appeared at all. However, because of its relationship to other variables in the model, the sales/total assets (S/TA) ratio ranks high in its contribution to the overall discriminating ability of the model. Still, there is a wide variation among industries and

across countries in asset turnover, and we will specify an alternative model (Z"), without X_5, at a later point.

Variables and their averages were measured at one financial statement prior to bankruptcy and the resulting F-statistics were observed; variables X_1 through X_4 are all significant at the 0.001 level, indicating extremely significant differences between groups. Variable X_5 does not show a significant difference between groups. On a strictly univariate level, all of the ratios indicate higher values for the nonbankrupt firms and the discriminant coefficients display positive signs, which is what one would expect. Therefore, the greater a firm's distress potential, the lower its discriminant score. Although it was clear that four of the five variables displayed significant differences between groups, the importance of MDA is its ability to separate groups using multivariate measures.

Once the values of the discriminant coefficients are estimated, it is possible to calculate discriminant scores for each observation in the samples, or any firm, and to assign the observations to one of the groups based on this score. The essence of the procedure is to compare the profile of an individual firm with that of the alternative groupings (distressed or non-distressed).

Testing the Model on Subsequent Distressed Firm Samples

In subsequent tests we examined 86 distressed companies from 1969-1975, 110 bankrupts from 1976-1995 and 120 bankrupts from 1997-1999. We found that the Z-Score model, using a cutoff score of 2.675, was between 82% and 96% accurate (see Figure 3). In repeated tests, the accuracy of the Z-Score model on samples of distressed firms has been in the vicinity of 80-90%, based on data from one financial reporting

period prior to bankruptcy. The Type II error (classifying the firm as distressed when it does not go bankrupt or defaults), however, has increased substantially in recent years with as much as 25% of all firms having Z-Scores below 1.81. Using the lower bound of the zone-of-ignorance (1.81) gives a more realistic cutoff Z-Score than the 2.675, although the latter resulted in the lowest overall error in the original tests. The model was 100% accurate when scores were below 1.81 or above 2.99.

Figure 3

Classification & Prediction Accuracy
Z-Score (1968) Credit Scoring Model*

Year Prior To Failure	Original Sample (33)	Holdout Sample (25)	1969-1975 Predictive Sample (86)	1976-1995 Predictive Sample (110)	1997-1999 Predictive Sample (120)
1	94% (88%)	96% (92%)	82% (75%)	85% (78%)	94% (84%)
2	72%	80%	68%	75%	74%

***Using 2.67 as cutoff score (1.81 cutoff accuracy in parenthesis)**

6. Adaptation for Private Firms' Application

One of the most frequent inquiries is "What should we do to apply the model to firms in the private sector?" Credit analysts, private placement dealers, accounting auditors, and firms themselves are concerned that the original model is only applicable to publicly traded entities (since X_4 requires stock price data). And, to be perfectly correct, the Z-Score model is a publicly traded firm model and *ad hoc* adjustments are not scientifically valid. For example, the most obvious modification is to substitute the book value of equity for the market value.

7. A Revised Z-Score Model

Rather than simply insert a proxy variable into an existing model to accommodate private firms, we advocate a complete reestimation of the model, substituting the book values of equity for the Market Value in X_4. One expects that all of the coefficients will change (not only the new variable's parameter) and that the classification criterion and related cutoff scores would also change. That is exactly what happens.

The result of our revised Z-Score model with a new X_4 variable is:

$$\mathbf{Z' = 0.717(X_1) + 0.847(X_2) + 3.107(X_3) + 0.420(X_4) + 0.998(X_5)}$$

The equation now looks somewhat different than the earlier model. Note, for instance, the coefficient for X_1 went from 1.2 to 0.7. But the model still looks quite similar to the one using the market value of equity.

8. Bond Rating Equivalents

One of the main reasons for building a credit-scoring model is to estimate the probability of default and loss given a certain level of risk estimation.[5] Although we all are aware that the rating agencies (e.g., Moody's, S&P, and Fitch) are certainly not perfect in their credit risk assessments, in general it is felt that they do provide important and consistent estimates of default - mainly through their ratings. In addition, since there has been a long history and fairly large number of defaults which had ratings, especially in the United States, we can "profit" from this history by linking our credit scores with these ratings and thereby deriving expected and unexpected PDs and perhaps LGDs. These estimates can be made for a fixed period of time from the rating date, e.g., one year, or on a cumulative basis over some investment horizon, e.g., five years. They can

[5] Indeed, Basel II's *Foundation* and *Advanced* Internal Rating Based Approaches require that these estimates be made based on the bank's or capital market experience

be derived from the rating agencies calculations, that is, from the so-called "static-pool" (S&P) or "dynamic-cohort" (Moody's) approaches. An alternative is to use Altman's [1989] mortality rate approach (updated annually) which is based on the expected default from the original issuance date and its associated rating.

With respect to nonrated entities, one can calculate a score, based on some available model, and perhaps link it to a bond rating equivalent. The latter then can lead to the estimate of PD. For example, in Figure 4 we list the bond rating equivalents for various Z-Score intervals based on average Z-Scores from 1995-1999 for bonds rated in their respective categories. One observes that triple-A bonds have an average Z-Score of about 5.0, while singe-B bonds have an average score of 1.70 (in the distressed zone).

The analyst can then observe the average one year PD from Moody's/S&P for B rated bonds and find that it is in the 5% - 6% range (Moody's [2002], S&P [2002]), or that the average PD one year after issuance is 2.45% (Altman and Arman, [2002]). Note that our mortality rate's first year's PD is considerably lower that the PD derived from a "basket" of Moody's/S&P B rated bonds which contain securities of many different ages and maturities. We caution the analyst to apply the correct PD estimate based on the qualities of the relevant portfolio of credit assets.

Figure 4

Average Z-Scores by S&P Bond Rating
1995 – 1999

	Average Annual Number of Firms	Average Z-Score	Standard Deviation
AAA	**11**	**5.02**	**1.50**
AA	**46**	**4.30**	**1.81**
A	**131**	**3.60**	**2.26**
BBB	**107**	**2.78**	**1.50**
BB	**50**	**2.45**	**1.62**
B	**80**	**1.67**	**1.22**
CCC	**10**	**0.95**	**1.10**

Source: Compustat Data Tapes, 1995-1999.

9. A Further Revision – Adapting the Model for Non-Manufacturers and Emerging Markets

The next modification of the Z-Score model assesses the characteristics and accuracy of a model without X_5 - sales/total assets. We do this in order to minimize the potential industry effect that is more likely to take place when such an industry-sensitive variable as asset turnover is included. In addition, we have used this model to assess the financial health of non-U.S. corporates. In particular, Altman, Hartzell and Peck [1995, 1997] have applied this enhanced Z" Score model to emerging markets corporates, specifically Mexican firms that had issued Eurobonds denominated in US dollars. The book value of equity was used for X_4 in this case.

The classification results are identical to the revised (Z' Score) five-variable model. The new Z" Score model is:

$$\mathbf{Z" = 6.56\ (X_1) + 3.26\ (X_2) + 6.72\ (X_3) + 1.05\ (X_4)}$$

Where Z"-Scores below 1.10 indicate a distressed condition.

All of the coefficients for variables X_1 to X_4 are changed as are the group means and cutoff scores. In the emerging market (EM) model, we added a constant term of +3.25 so as to standardize the scores with a score of zero (0) equated to a D (default) rated bond. See Figure 5 for the bond rating equivalents of the scores in this model. We believe this model is more appropriate for non-manufacturers than is the original Z-Score model. Of course, models developed for specific industries, e.g., retailers, telecoms, etc. are an even better method for assessing distress potential of like-industry firms.

Figure 5 US Bond Rating Equivalent Based on EM Score $Z''=3.25 + 6.56 (X_1) + 3.26 (X_2) + 6.72 (X_3) + 1.05 (X_4)$	
US Equivalent Rating	**Average EM Score**
AAA	8.15
AA+	7.60
AA	7.30
AA-	7.00
A+	6.85
A	6.65
A-	6.40
BBB+	6.25
BBB	5.85
BBB-	5.65
BB+	5.25
BB	4.95
BB-	4.75
B+	4.50
B	4.15
B-	3.75
CCC+	3.20
CCC	2.50
CCC-	1.75
D	0
Source: In-Depth Data Corp.; average based on more than 750 U.S. Corporates with rated debt outstanding: 1995 data.	

10. Macro Economic Impact and Loss Estimation

All of the aforementioned models are, in a sense, static in nature in that they can be applied at any point in time regardless of the current or expected performance of the economy and the economy's impact on the key risk measures: (1) Probability of Default (PDs), and (2) Loss Given Default (LGDs). Aggregate PDs vary over time so that a firm with a certain set of variables will fail more frequently in poor economic times and vice-versa in good periods. This systematic factor is not incorporated directly in the establishment of scoring models in most cases. Some recent attempts have included experimenting with variables which can capture these exogenous factors - like GDP

growth. Since GDP growth will be the same for the good firms as well as the distressed ones in the model development phase, it is necessary to be creative in including macro-impact variables. One idea is to add an aggregate default measure for each year to capture a high or low risk environment and observe its explanatory power contribution in the failure classification model. Such attempts have only achieved modest success to date. An alternative structure is to assign prior probabilities of group membership (for examples, default/ non-default), as well as costs of errors, to determine optimal cutoff scores in the model (see Altman, et al. (1977) for a discussion of this technique).

11. Loss Given Default Estimates (Default Recoveries)

Most modern credit risk models and all of the VaR models (e.g., CreditMetrics®), assume independence between PD and the recovery rate on defaulted debt. Altman, Brady, Resti and Sironi [2002] however, show that this is an incorrect assumption and simulate the impact on capital requirements when you factor in a significant negative correlation between PD and recovery rates over time. In particular, the authors found that in periods of high default rates on bonds, the recovery rate is low relative to the average and losses can be expected to be greater (e.g., in 2000 and 2001) when bond recoveries (prices just after default) were 26.4% and 25.5%, respectively (Altman and Arman, 2002). Hu and Perraudin [2002] find similar results and Frye [2000] specified a systematic macro-economic influence on recovery rates. This has caused serious concern among some central bankers of the potential procyclicality of a rating based approach, which is the approach being recommended by Basel II. In addition, investors in risky corporate debt and collateralized debt obligations (CDOs) need to be aware that recoveries will usually be lower in high default periods.

Basel II, however, has made a real contribution by motivating an enormous amount of effort on the part of banks (and regulators) to build (evaluate) credit risk models that involve scoring techniques, default and loss estimates, and portfolio approaches to the credit risk problem. We now turn to an alternative approach to the Z-Score type models.

12. The Expected Default Frequency (EDF) Model

KMV Corporation, purchased by Moody's in 2002, has developed a procedure for estimating the default probability of a firm that is based conceptually on Merton's [1974] option-theoretic, zero-coupon, corporate bond valuation approach. The starting point of the KMV model is the proposition that when the market value of a firm drops below a certain liability level, the firm will default on its obligations. The value of the firm, projected to a given future date, has a probability distribution characterized by its expected value and standard deviation (volatility). The area under the distribution that is below the book liabilities of the firm is the PD, called the EDF . In three steps, the model determines an EDF for a company. In the first step, the market value and volatility of the firm are estimated from the market value of its stock, the volatility of its stock, and the book value of its liabilities. In the second step, the firm's default point is calculated relative to the firm's liabilities coming due over time. A measure is constructed that represents the number of standard deviations from the expected firm value to the default point (the distance to default). Finally, a mapping is determined between a firm's distance to default and the default rate probability based on the historical default experience of companies with similar distance-to-default values.

In the case of private companies, for which stock price and default data are generally unavailable, KMV estimates the value and volatility of the private firm directly from its observed characteristics and values based on market comparables, in lieu of market values on the firm's securities.

For a firm with publicly traded shares, the market value of equity may be observed. The market value of equity may be expressed as the value of a call option as follows:

Market value of equity = f (book value of liabilities,
market value of assets,
volatility of assets, time horizon)

Next, the expected asset value at the horizon and the default point are determined. An investor holding the asset would expect to get a payout plus a capital gain equal to the expected return. Using a measure of the asset's systematic risk, KMV determines an expected return based upon historic asset market returns. This is reduced by the payout rate determined from the firm's interest and dividend payments. The result is the expected appreciation rate, which when applied to the current asset value, gives the expected future value of the assets. It was assumed that the firm would default when its total market value falls below the book value of its liabilities. Based upon empirical analysis of defaults, KMV has found that the most frequent default point is at a firm value approximately equal to current liabilities plus 50% of long-term liabilities (25% was first tried, but did not work well).

Given the firm's expected value at the horizon, and its default point at the horizon, KMV determines the percentage drop in the firm value that would bring it to the default point. By dividing the percentage drop by the volatility, KMV controls for the

effect of different volatilities. The number of standard deviations that the asset value must drop in order to reach the default point is called the distance to default

The distance-to-default metric is a normalized measure and thus may be used for comparing one company with another. A key assumption of the KMV approach is that all the relevant information for determining relative default risk is contained in the expected market value of assets, the default point, and the asset volatility. Differences because of industry, national location, size, and so forth are assumed to be included in these measures, notably the asset volatility.

Distance to default is also an ordinal measure akin to a bond rating, but it still does not tell you what the default probability is. To extend this risk measure to a cardinal or a probability measure, KMV uses historical default experience to determine an expected default frequency as a function of distance to default. It does this by comparing the calculated distances to default and the observed actual default rate for a large number of firms from their proprietary database. A smooth curve fitted to those data yields the EDF as a function of the distance to default.

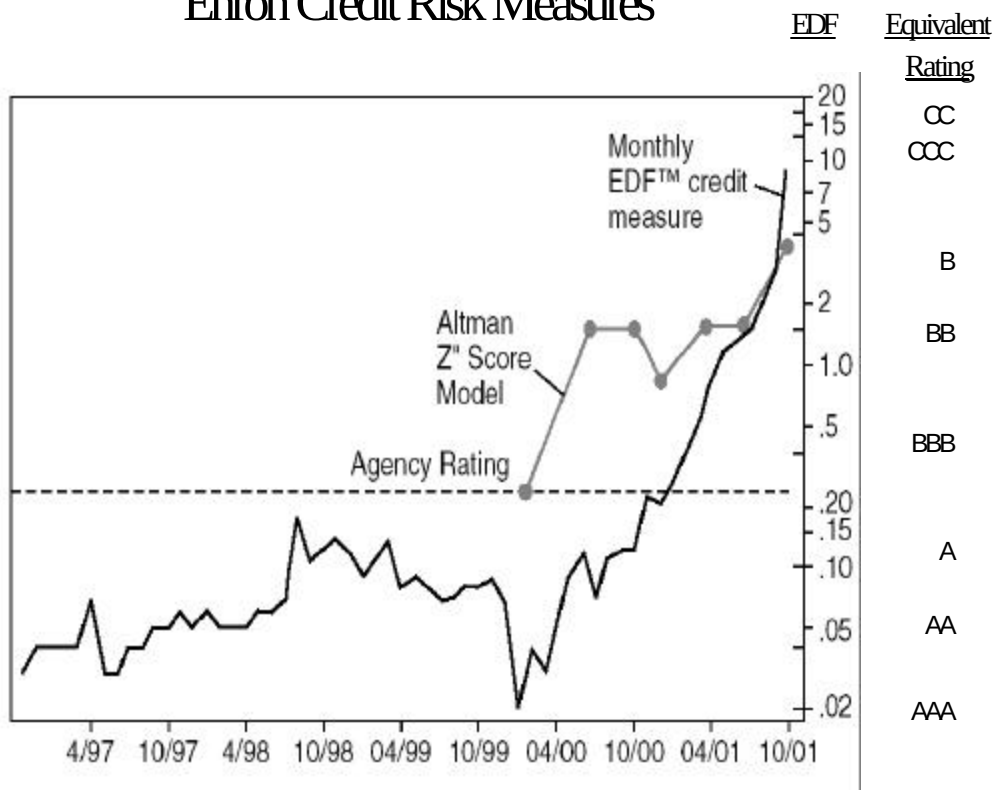
11. The Enron Example: Models Versus Ratings

We have examined two of the more popularly found credit scoring models - the Z-Score model and KMV's EDF - and in both cases a bond rating equivalent can be assigned to a firm. Many commentators have noted that quantitative credit risk measurement tools can save banks and other "investors" from losing substantial amounts or at least reducing their risk exposures. A prime example is the recent Enron debacle, whereby billions of dollars of equity and debt capital have been lost. The following illustrates the potential savings involved from a disciplined credit risk procedure.

On December 2, 2001, Enron Corporation filed for protection under Chapter 11 and became the largest corporate bankruptcy (at that time) in U.S. history - with reported liabilities at the filing of more than $31 billion and off-balance sheet liabilities bringing the total to over $60 billion! Using data that was available to investors over the period 1997-2001, Figure 6 (from Saunders and Allen [2002]) shows the following: KMV's EDF, with its heavy emphasis on Enron's stock price, rated Enron AAA as of year-end 1999, but then indicated a fairly consistent rating equivalent deterioration resulting in a BBB rating one year later and then a B- to CCC+ rating just prior to the filing. Our Z"Score model (the four variable model for non-manufacturers) had Enron as BBB as of year-end 1999 - the same as the rating agencies - but then showed a steady deterioration to B as of June 2001. So, both quantitative tools were issuing a warning long before the bad news hit the market. Although neither actually predicted the bankruptcy, these tools certainly could have provided an unambiguous early warning that the rating agencies were not providing (their ratings remained at BBB until just before the bankruptcy). Both models were using a vast under-estimate of the true liabilities of the firm. If we use the true liabilities of about $60 billion, both models would have predicted severe distress. To be fair, the rating agencies were constrained in that a downrating from BBB could have been the death-knell for a firm like Enron which relied on its all important investment grade rating in its vast counterparty trading and structured finance transactions. An objective model, based solely on publicly available accounting and market information, is not constrained in that the analyst is free to follow the signal or to be motivated to dig-deeper into what on the surface may appear to be a benign situation.

Figure 6

Enron Credit Risk Measures



Source: **Saunders & Allen [2002].**

WorldCom – A Case of Huge Indirect Bankruptcy Costs

A second high-profile bankruptcy that we have applied the two credit scoring models to is WorldCom—the largest Chapter 11 bankruptcy in our nation's history with over $43 billion of liabilities at the time of filing. WorldCom, one of the many high flying telecommunications firms that have succumbed to bankruptcy in the last few years, but one with substantial real assets, was downgraded from it's A- rating to BBB+ in 2001 and then to "junk" status in May 2002, finally succumbing shortly thereafter and filing for bankruptcy protection in mid-July.

We performed several tests on WorldCom including the Z"-Score (four variable model) which is more appropriate for non-manufacturers and the KMV-EDF risk measure. The Z-Score tests were done on the basis of three sets of financials: (1) the *unadjusted* statements available to the public before the revelations of massive understatements of earnings and the write-offs of goodwill, (2) *adjusted* for the first acknowledgement of $3.85 billion of inflated profits in 2001 and the first quarter of 2002 and (3) *adjusted* for a further write-off of $3.3 billion and a massive write-off of $50 billion in assets (goodwill). These results are shown in Figure 7.

Our results show that the Z"-Score (using unadjusted data) was 1.50 (4.75 with the constant term of 3.25 added to get our bond equivalent score [BES]) at the end of 2000. This translates to a BB- rating. The EDF measure as of year-end 2000 was equivalent to BBB-/BB+. At that time, the actual S&P rating was A-. The BES remained essentially the same, or even improved a bit, throughout 2001, as did the EDF, when the rating agencies began to downgrade the company to BBB+. At the end of Q1-2002, the last financials available before its bankruptcy, WorldCom's Z"-Score was 1.66

(4.91 BES) and it remained a BB- Bond equivalent. The EDF rose and its rating equivalent also fell to about BB- by March 2002 and continued to drop to CCC/CC by June, when the S&P rating dropped to BB and then to CCC just before default. So, while both models were indicating a non-investment grade company as much as 18 months before the actual downgrade to non-investment grade and its eventual bankruptcy, we would not have predicted its total demise based on the available financials. But it did go under, primarily because of the fraud revelations and its attendant costs due to the loss of credit availability. We refer to these "costs" as indirect bankruptcy costs, usually associated with the public's awareness of a substantial increase in default probability (see Altman, 1984). This is a classic case of the potential enormous impact of these hard-to-quantify costs and is a clear example of where the *expected* costs of bankruptcy overwhelm the expected tax benefits from the debt.

Under the second scenario, we reduce earnings, assets and net worth by $3.85 billion over the five quarters ending the first quarter of 2002. The resulting Z"-Score was 1.36 (4.61 BES) as of year-end 2001 – a B+ bond equivalent – and 4.55 as of Q1-2002 - again a B+ equivalent.[6] While the revised rating equivalent is lower, we still would not have predicted WorldCom to go bankrupt, even with the adjusted financials.

After adjusting for the "second installment" of improper accounting of profits and a massive write-off of goodwill,[7] the resulting bond rating equivalent is now lower (CCC+) but still not in the default zone.

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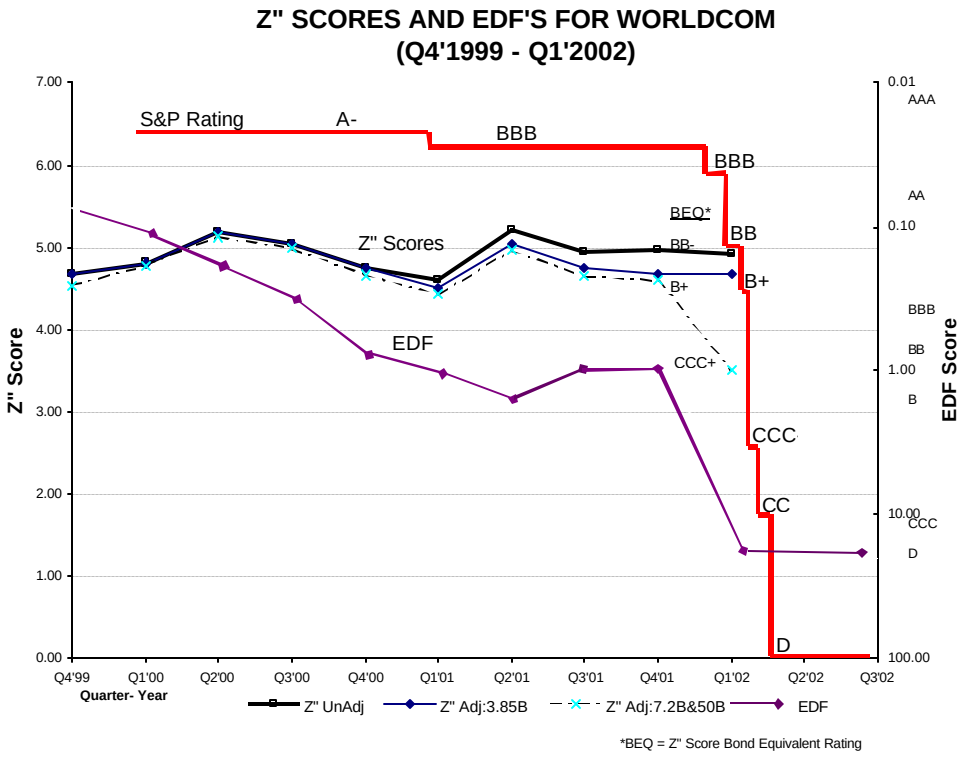
[6] WorldCom's Z-Score (original five-variable model) was 1.7 as of Q1-2002, a B rating equivalent, but in the distress zone.

[7] Actually, the Z-Score models should only consider tangible assets, so the goodwill should not, in a strict sense, have been considered even in the unadjusted cases.

Figure 7



Sources: Compilation by the author (E. Altman, NYU Stern), the KMV (Moody's) Website and Standard & Poor's Corporation.

14. Conclusion

In the Enron and WorldCom cases, and many others that we are aware of, although tools like Z-Score and EDF were available, losses were still incurred by even the most sophisticated investors and financial institutions. Having the models is simply not enough! What is needed is a "credit-culture" within these financial institutions, whereby credit risk tools are "listened-to" and evaluated in good times as well as in difficult situations. And, to repeat an important caveat, credit scoring models should not be the only analytical process used in credit decisions. The analyst will, however, when the indications warrant, be motivated to consider or re-evaluate a situation when traditional techniques have not clearly indicated a distressed situation.

References

Altman, E., 1968, "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy," **Journal of Finance**, September, pp. 189-209.

Altman, E., 1984, "A Further Empirical Investigation of Bankruptcy Costs," **Journal of Finance**, September, pp. 1067-89.

Altman, E., 1989, "Measuring Corporate Bond Mortality and Performance," **Journal of Finance**, September, pp. 909-922.

Altman, E., 1993, **Corporate Financial Distress and Bankruptcy**, Second Edition, John Wiley & Sons, New York.

Altman, E., and P. Arman, 2002, "Defaults and Returns in the High Yield Bond Market," **Journal of Applied Finance**, Spring-Summer, pp 98-112.

Altman, E., and A. C. Eberhart, 1994, "Do Seniority Provisions Protect Bondholders' Investments," **Journal of Portfolio Management**, Summer, pp. 67-75.

Altman, E., R. Haldeman, and P. Narayanan, 1977, "ZETA Analysis: A New Model to Identify Bankruptcy Risk of Corporations," **Journal of Banking and Finance**, June, pp. 29-54.

Altman, E., J. Hartzell, and M. Peck, 1995, "Emerging Markets Corporate Bonds: A Scoring System," (New York, Salomon Brothers Inc), Reprinted in the *Future of Emerging Market Flows*, edited by R. Levich, J.P. Mei, 1997, Kluwer, Holland.

Altman, E., B. Brady, A. Resti, and A. Sironi, 2002, "The Link Between Default Rates and Recovery Rates: Implications for Credit Risk Models and Procyclicality," NYU Salomon Center, WP #S-02-9 and Altman, Resti and Sironi," Analyzing and Explaining Default Recovery Rates," **ISDA**, January 2002.

Basel Commission on Banking Supervision, 1999, "Credit Risk Modeling: Current Practices and Applications," **BIS**, June.

Basel Commission on Banking Supervision, 2001, The Basel Capital Accord," **BIS**, January.

Beaver, W., 1966, "Financial Ratios as Predictors of Failures," in **Empirical Research in Accounting**, selected studies, pp. 71-111.

Beaver, W., 1968, "Alternative Accounting Measures as Predictors of Failure," **Accounting Review**, January, pp. 46-53.

Frye, J., 2000, "Collateral Damage," **Risk**, April.

Hu, Y.T. and W. Perraudin, 2002, "The Dependency of Recovery Rates of Corporate Bond Issues," **Birkbeck College**, Mimeo, February.

Kealhofer, S., 2000, "The Quantification of Credit Risk," **KMV Corporation**, San Francisco, CA, January (unpublished).

KMV, 2000, "The KMV EDF Credit Measure and Probabilities of Default," San Francisco, CA, **KMV Corporation**.

McQuown, J.A., 1993, "A Comment on Market vs. Accounting Based Measures of Default Risk," KMV Corporation, San Francisco, CA.

Merton, R.C., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates," the **Journal of Finance**, June, pp. 449-470.

Moody's, Annually, "Corporate Bond Defaults and Default Rates," *Special Report*, Moody's Investor Services, January.

Saunders, A., and L. Allen, 2002, **Credit Risk Measurement**, Second Edition (New York) John Wiley & Sons.

Shumway, T., 2002, "Forecasting Bankruptcy More Accurately: A Simple Hazard Model," **TMA Advanced Education Workshop**, Boston College, MA, June 21.

Standard & Poor's, Annually, "Rating Performance: Stability and Transition," *Special Report*, updated annually, New York City, S&P Corporation.