Special Comment

December 2004

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A User's Guide to Moody's Default Predictor Model: an Accounting Ratio Approach

In order to improve the quality of their dialogue with market participants, Moody's analysts access a range of competing opinions, such as credit risk assessments implied from bond yield spreads and credit default swap spreads, Expected Default Frequencies (EDFs) from Moody's-KMV models, and credit opinions issued by market analysts and other rating agencies. We introduce in this paper another basis of opinion, Moody's Default Predictor (MDP), which is derived from a model which predicts default risk over a one-year horizon for public, non-financial firms using accounting-based ratios.

Although accounting-based statistical models typically lack a compelling theoretical framework for determining the appropriate variables and relationships, they do provide an alternative credit view that is not based on market opinion and driven by many of the same variables considered by most credit analysts.[1] MDPs can be used to:

- Analyze rating consistency across sectors, geography and time.
- Spot "outliers".
- Contribute toward baseline rating estimates for unrated issuers.
- Guide analysts towards the most powerful indicators of credit risk.
- Facilitate discussions with users of Moody's ratings.

A key feature setting the one-year MDP model apart from other modeling efforts is the exclusion of market pricing information. Accounting ratio-based analysis provides an assessment of creditworthiness not based on market prices. Market prices may indeed be informed by accounting ratios (and other information which Moody's considers in performing its fundamental analysis), but also contain time-varying risk and liquidity premiums that may obscure information about creditworthiness in terms of pure default prediction.

This document provides an overview of the methodology underpinning the construction of the MDP model.

1. *Whether the MDPs are "statistically independent" of default probability estimates derived from market pricing information is an interesting question beyond the scope of this paper.*

To summarize our modeling and testing methodology:

- *Data sample*. We choose as our objective the estimation of default risk for US non-financial firms holding a Moody's ratings during the years 1989 through 2002. Reliable data on bond defaults for this sample is contained in Moody's Default Risk Database.[2] Annual financial data was obtained from COMPUSTAT.
- *Time frame*. The model predicts default likelihood over a one-year horizon. Although a longer horizon would be more appropriate if the goal were to mimic agency ratings (which encompass multiple horizons), the effective sample size available for model estimation falls rapidly as the horizon is lengthened.[3]
- *Modeling technique*. After examining many approaches, we settled on a data transformation method as described in Falkenstein, et al. (2000).[4] While developed for small, non-public firms, we find the technique well suited to large public firms. Consistent with other recent academic efforts, we use probit regression analysis to estimate the statistical model.
- *Model validation*. Standard statistical methods are not geared towards measuring overall model accuracy, in or out of sample. We rely instead on power curves and accuracy ratio statistics to gauge the ability of the model to discriminate between firms who subsequently default and those who do not.

Methodology

We compiled a financial data set for rated US non-financial firms and matched this against default data from Moody's Default Research Database. The fiscal year end (FYE) 1989 – 2001 sample period encompasses two recessions. We set aside FYE 2001 observations for model validation, and estimated the model using FYE 1989 – 2000 data. This provided a testing population of 14,176 firm-years, including 371 defaults, and a hold-out sample of 1,378 firms and 60 defaults. The median number of firms in each year was 1,167, and the median number of firm-years per firm in the testing set was 6 years. The average number of new firms per year was 34.

We confined the independent variables tested to those derivable from the published COMPUSTAT financial database. Such data is readily available for large numbers of debt issuers. On the other hand, many non-financial indicators may in fact be highly correlated with subsequent economic distress. But such data is usually difficult to quantify objectively. For example, poor corporate governance is often linked to a propensity to commit fraud or otherwise engage in financial self-dealing. Yet, there are no widely accepted, quantifiable measures of corporate governance.

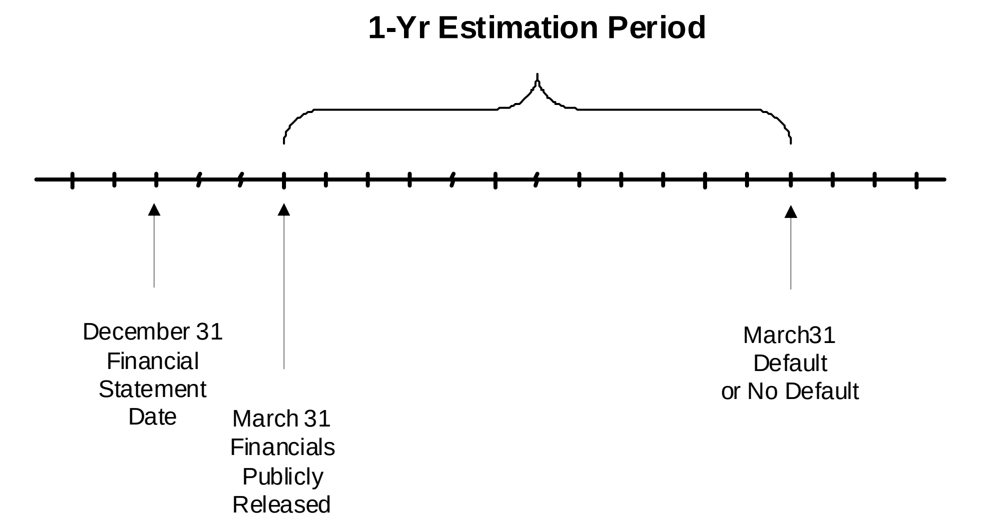
The independent variables (ratios) were drawn from a list of 43 proxies for coverage, leverage, profitability, liquidity, scale, growth and volatility. Many of these are widely used by credit analysts. Please see the Appendix for a list of the variables tested.

TIME ALIGNMENT

Each variable was calculated as of a particular firm's statement date or fiscal year end. In order to relate this observation date to a subsequent default (or non-default) event, we chose a timing window that accounted for the availability of data to a hypothetical user. Because most firms release complete financial statement data months after the close of a statement period, full information about firm performance is typically not available at the closing date. To match the lag in information flow, we shift the estimation period by three months to guarantee financial statements would have been filed and therefore publicly available before the start of the default estimation period (please see Figure 1).

2. *We define default as either a missed interest payment, filing for bankruptcy or completing a distressed exchange (where bondholders suffer some form of economic loss).*
3. *Altman, Edward and Herbert Rijken, "How Rating Agencies Achieve Rating Stability," in Cantor, R. (Ed.), Recent Research on Credit Ratings (special issue). Journal of Banking and Finance, 28 (11), show that the estimated coefficients of the familiar z-score default prediction model change substantially as the horizon is lengthened and more closely resemble the coefficients of a model designed to predict agency credit ratings.*
4. *Please see Falkenstein, Eric, Andrew Boral and Lea V. Carty, "RiskCalc Private Model: Moody's Default Model for Private Firms," Moody's Global Credit Research, May 2000.*

Figure 1

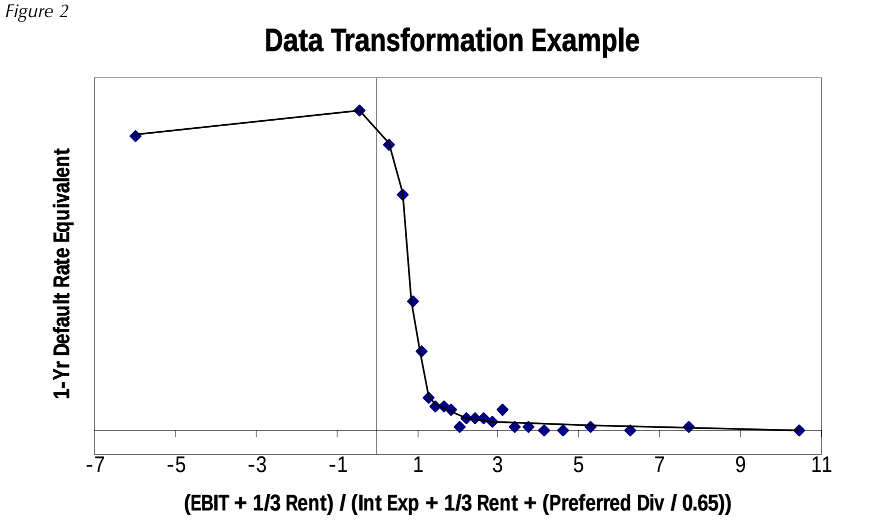


DATA TRANSFORMATION

In order to accommodate nonlinear relationships between an individual ratio and default risk, we use an empirical transformation technique to convert each ratio value into a default-rate equivalent. The technique involves ordering the values of each ratio across the testing population from smallest to largest, and creating equal-sized groupings, or buckets, based on this ordering. For example, the lowest 5% of ratio values might form the first bucket; the next 5% might form the second bucket; and so on. Within each bucket, a default rate is calculated by dividing the number of defaults associated with that bucket by the total number of firm-years that make up the bucket. This default rate is paired with the calculated average ratio value for the bucket and graphically plotted in order to estimate a univariate default-rate equivalent transform function.[5]

Figure 2 illustrates the process for the coverage ratio (EBIT + 1/3 Rent) / [Interest Expense + 1/3 Rent + (Preferred Dividend / 0.65)]. Each bucket is represented by a point on the graph, and the fitted nonlinear curve through the points represents the transform function used to convert the ratio into a univariate default-rate equivalent. To curb the distortions caused by outliers, extreme ratio values are capped at levels corresponding to the right and left end-points of the mapping.

Figure 2



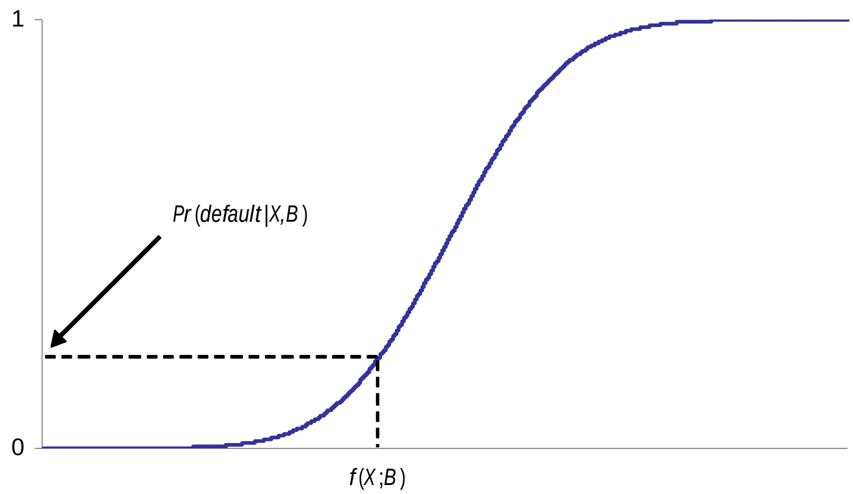
5. *We do not assume that each transform will be static throughout time and will re-estimate periodically.*

MODEL ESTIMATION

To estimate the final model, we use the transformed, univariate default-rate equivalents for each ratio as dependent variables in a probit regression. A probit model is a binary choice model where the dependent variable can assume just two possible values. In our case, the dependent variable represents default within a one-year horizon and so we assign a value of 1 for companies defaulting in this period and 0 for non-defaulting companies. Probit regression uses an S-shaped transform, mirroring the standard cumulative normal distribution, in order to estimate the relationship between independent variables and a dependent variable. This transform is bounded below by 0 and above by 1.[6]

Figure 3

The Probit Function



In its general form the default-based probit model can be expressed as:

$$y = \Pr(default \mid X; B) = \int_{-\infty}^{f(X;B)} \frac{1}{\sqrt{2\pi}} \exp\left[-\frac{z^2}{2}\right] dz$$

where

$$f(X;B) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_n x_n$$

In words, the probability of default, given a set of independent variables *X* and parameter estimates *B*, is the integral over the standard normal density function between minus infinity and a linear combination of the selected independent variables.[7] The output of the model, which we refer to as a probit "score," is dependent solely upon the value taken by the function f(*X*; *B*), which in turn depends upon each of the variable inputs (x_i's) and each of the estimated parameters (β_i's). A maximum likelihood estimation technique is used to estimate the parameters. As shown in Figure 3, the model output is monotonic in f(*X*; *B*): larger values lead to higher scores and smaller values lead to smaller scores.

6. *Whether or not a probit transform represents the appropriate, or correct, relationship between our dependent and independent variables is an empirical question that we leave for others. We admittedly use it here, in part, out of convenience.*
7. *The output of the probit model does not produce an exact probability of default because of a bias in the distribution around the tails. However, one can use an empirical mapping, based on model outputs, to derive adjusted default rate estimates.*

The probit model establishes a relationship between the probability of default and the selected independent variables. In our model, however, the independent variables used are themselves functions of other variables. This is because we use the default-rate equivalent implied by each ratio rather than the ratio itself. In the Data Transformation section we described the process used to transform a ratio value into its default-rate equivalent. This process is itself an empirically derived transformation. Consequently, we redefine f(*X; B*) as:

$$f(X;B) = \beta_0 + \beta_1 T_1(x_1) + \beta_2 T_2(x_2) + \cdots + \beta_n T_n(x_n)$$

where $T_i(x_i)$ is the default-rate equivalent transformation function of ratio x_i.

Using the ratio values themselves, rather than their default-rate equivalents, would produce a much weaker model because many ratios do not exhibit a linear relationship with default risk. For example, we have found that both very high and very low income volatility have been associated with elevated default rates, while intermediate values are associated with lower default rates. Because it would not establish a monotonic relationship between growth and default risk, the probit model would likely reject income growth as a risk factor. By transforming the ratios into their default-rate equivalents, the nonlinearities are removed and a more accurate model is estimated.[8]

MAPPING TO RATINGS

To facilitate comparison with other measures, the probit score value is mapped to an implied letter rating. This is done by matching the frequency distribution of Moody's estimated Senior Unsecured ratings (over the training and validation samples) with an ordinal ranking of probit scores.[9,10] If, for example, 5% of firm-years in the combined sample held a "Aaa" Moody's rating, then the lowest 5% of probit scores in the combined sample would be given a "Aaa" MDP implied rating, and so on.

Results

Starting with a probit model containing 43 standard and modified ratios, we followed a reverse step-wise procedure by deleting each variable in turn, based on statistical significance. Initially, we were non-discriminatory in the elimination process. All preconceived ideas about ratios that should drive default risk were ignored. Eventually, however, we faced variable selection decisions that could not be guided by statistical methods. Instead, analyst preference and prior modeling studies were used to guide the final selection of ratios.

We finally selected six explanatory variables, each of which is significant in the one-year MDP model.[11] They are, in descending order of significance:

Table 1

One-Year Default Prediction: Significant Variables

Ratio
(EBIT + 1/3 Rent) / [Interest Expense + 1/3 Rent + (Preferred Dividend / 0.65)]
Adjusted Debt / Adjusted Book Capital
(Cash + Equivalents) / Total Assets
5-Year Revenue Volatility
Retained Cash Flow / Adjusted Debt
Asset Growth

Using multivariate probit regression analysis, it is difficult to describe the relationship between select independent variables and the dependent variable. This is because changes in any one independent variable can have differing impacts on the dependent variable depending upon the levels of the other independent variables. For example, a change in liquidity would have a different impact on the default probability estimate depending upon whether leverage

8. *This higher level of accuracy does come at a cost. By using the default-rate equivalents instead of the ratios we decrease the degrees of freedom of the model, since the default-rate equivalent is a function of its respective ratio. Further, the model may suffer from "over-fitting" since the transform functions are estimated over the in-sample dataset. We use out-of-sample testing to check for this.*
9. *MDP implied ratings are a relative rank ordering of one-year default risk, while Moody's Senior Unsecured Ratings are a relative rank ordering of time-invariant credit risk.*
10. *In order to produce the best possible rating prediction model, one could employ a simple linear regression model with a dependent variable that takes on 21 possible values, rather than the 0, 1 (no default / default) values used in a default prediction model. As with the transform functions, we do not assume that this mapping will be static over time and will recalibrate periodically.*
11. *By chance alone, at least one out of 43 randomly-chosen variables would be likely to appear significant. The probability of six emerging as significant (at the 5% level) is 1.9%.*

was high or low. In a linear regression model, a given change in liquidity will have the same impact on the default probability estimate for any fixed value of leverage.

Thus, in order to fully describe the relationship between a single independent variable and the dependent variable, one needs to dynamically alter the levels of all other independent variables in the model. Instead, we plot the relationship between each independent variable and the dependent variable, holding all other independent variables constant at their median values.

Figure 4

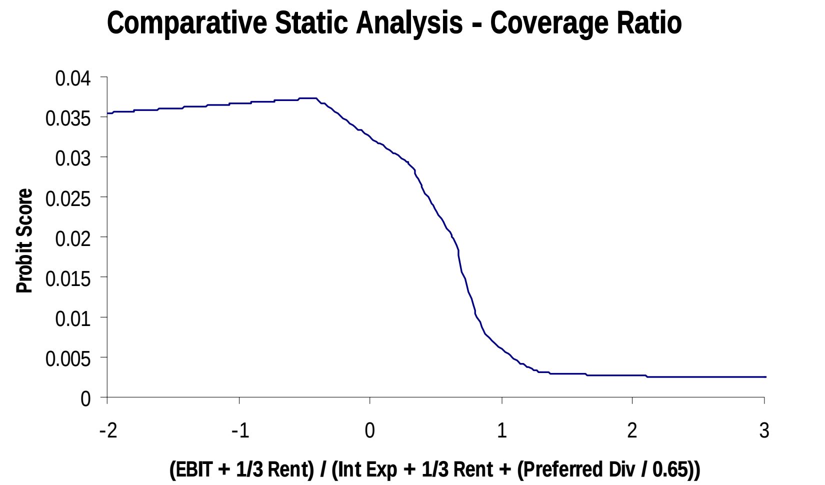


Figure 4 displays the relationship between the most significant (untransformed) variable in the one-year MDP model, (EBIT + 1/3 Rent) / [Interest Expense + 1/3 Rent + (Preferred Dividend / 0.65)], and the probit score. Note that the relationship for this interest coverage measure is not perfectly monotonic. Extreme negative values empirically show lower default risk than small negative values, possibly because such negative values are typically caused by low interest expense rather than excessive negative EBIT values. Positive coverage values, as one might expect, do exhibit a monotonically decreasing relationship. The relationship is most dramatic in the interval -0.4 to 1.3. Also note the strong similarity between Figure 4 and the univariate transform of the coverage variable shown in Figure 2. By passing the relationship through the cumulative normal function, we do not alter its basic shape.

Figure 5

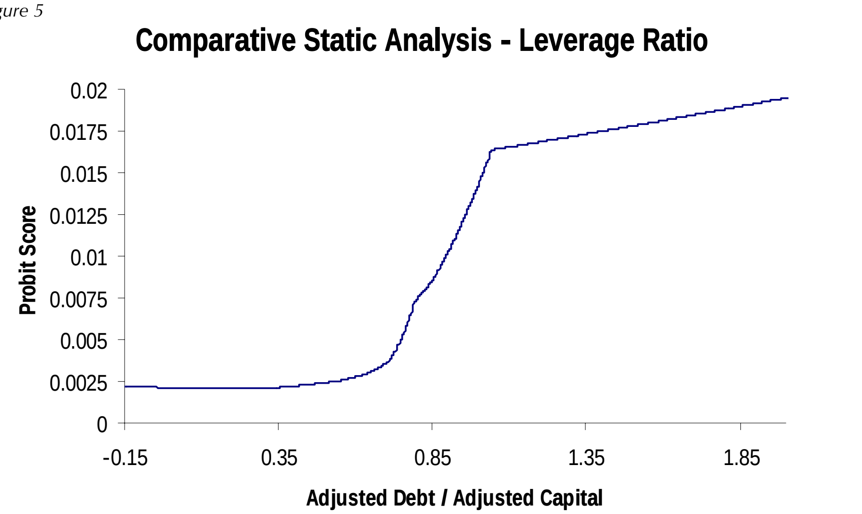


Figure 5 charts the relationship between the probit score and the second most significant variable in the MDP model, Adjusted Debt / Adjusted Capital, a measure of leverage. The relationship is nearly exponential between negative infinity and 1.1, after which, increases in predicted default risk are less pronounced as leverage rises.

Figure 6

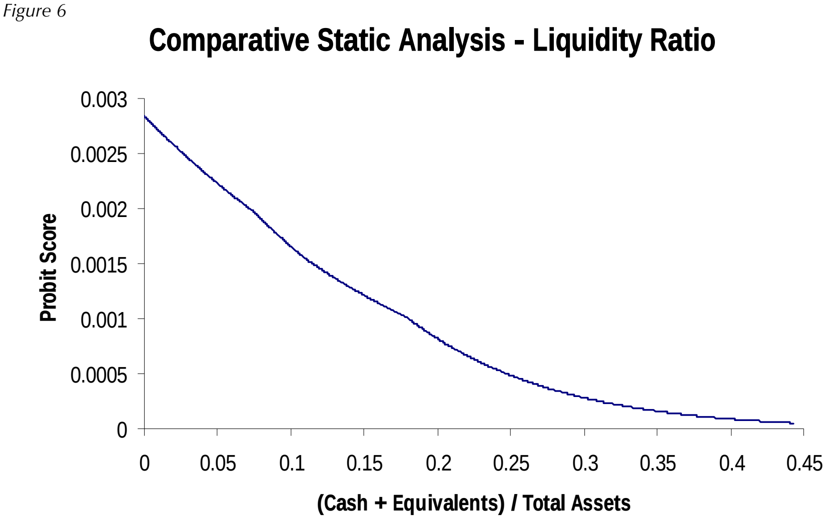


Figure 6 plots the behavior of (Cash + Equivalents) / Total Assets, a liquidity measure. Note the smooth, decreasing monotonic relationship that approaches the asymptote beyond values of 0.4.

Figure 7

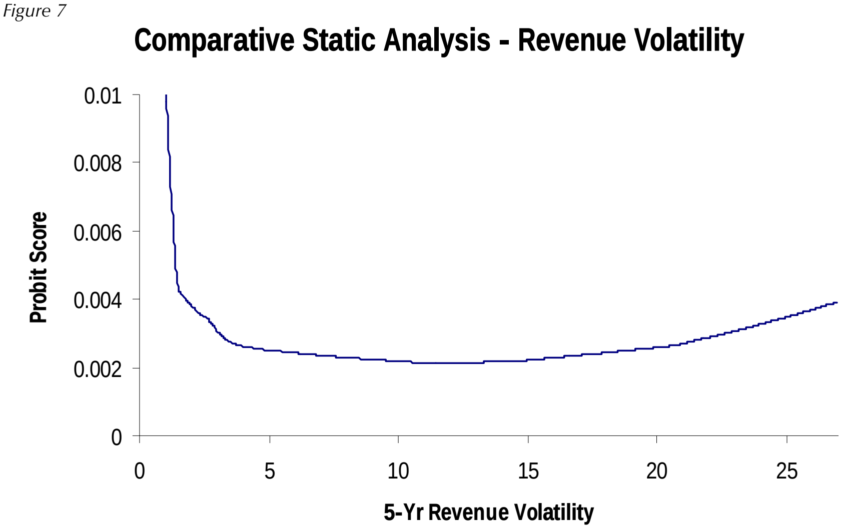


Figure 7 plots the probit score against a 5-year volatility measure. Volatility is calculated by averaging revenue over five years and dividing this by the standard deviation of revenue over the same period. This measure of volatility is not typically found in the average analyst's toolkit.[12] The relationship depicted is "U-shaped", where both high and low values of the ratio have relatively high predicted default risk, while middle-range values have relatively low predicted default risk. The relationship is not perfectly "U-shaped" though since extreme low values of the ratio are associated with greater default risk than are extreme high values.

12. *We are trying to capture the notion that, all else equal, a firm with more volatile revenue has higher default risk.*

Figure 8

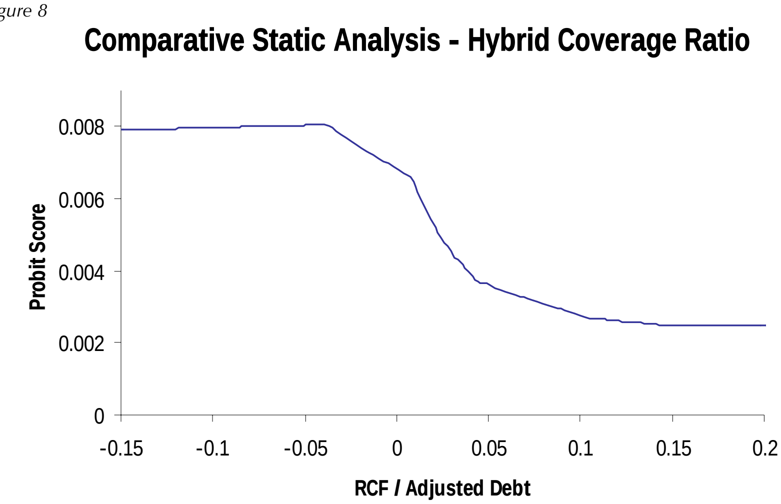


Figure 8 shows the results for Retained Cash Flow/Adjusted Debt, a hybrid debt-coverage measure that can be interpreted as the number of years required to pay down debt from operations. The shape is very similar to that shown above for interest coverage, including the upward slope for most negative values and downward slope for positive values.

Figure 9

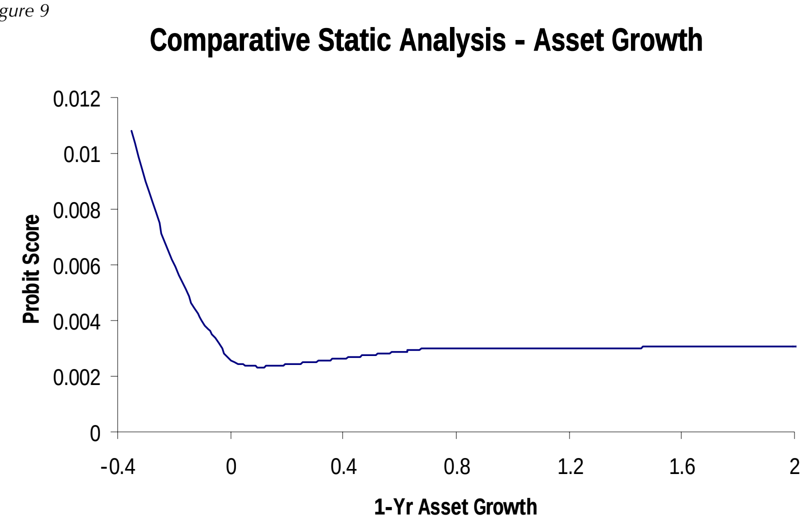


Figure 9 illustrates the relationship between the probit score and the one-year growth rate of Total Assets. The L-shape implies that large positive growth, while slightly more risky than moderate growth, is not as risky as negative growth.

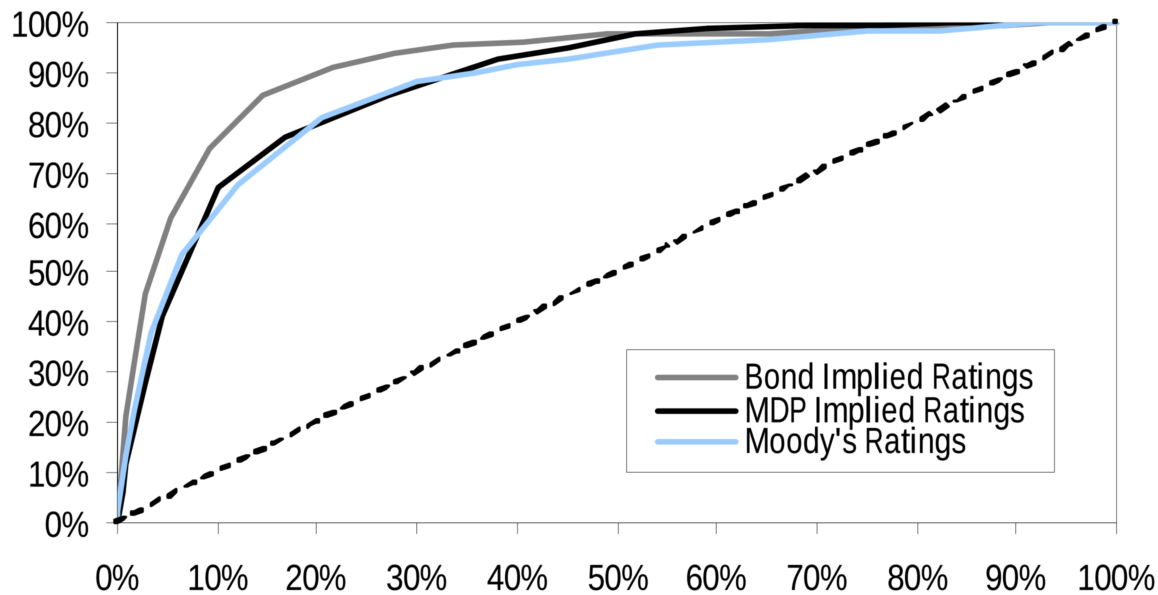
Model Accuracy

In order to validate the predictive performance of statistical models, we rely on standard accuracy measures. The most widely-used tool for assessing a model's ability to correctly rank-order *ex-post* default risk is the *Cumulative Accuracy Profile* (CAP). Depicted graphically, a CAP curve is a type of Lorenz Curve and shows the cumulative percent of observed defaults attributed to a ranking of observations by risk scores (or any other ranking system, such as bond ratings).

Figure 10 illustrates the MDP model's CAP curve for the years 1999 through 2003 using quarterly observations taken from Moody's Market Implied Ratings™ (MIR) Database. The MIR database contains MDP implied ratings for a larger set of issuers than the MDP model was originally trained and validated on and contains more recent observations. We include for comparison, and over a matched-pair dataset, CAP curves derived from a risk ranking implied by option-adjusted yield spreads (OAS) on each issuer's traded bonds and from a risk ranking based on Moody's estimated Senior Unsecured Ratings.[13] Although the MDP model was trained and validated using annual financial data, the MDP model's CAP curve shown in Figure 10 is constructed using trailing four-quarter financial data.

Figure 10

Cumulative Accuracy Profiles
1999 - 2003 Sample



The horizontal axis in Figure 10 represents the percentile risk score and places the lowest rated issuers on the left and the highest to the right. The vertical axis shows the cumulative share of all defaults (one year later) for each percentile risk score. A so-called perfect model, one that anticipated all defaults and assigned them the lowest possible score, would be represented by a near-vertical line reaching from the origin to the upper left corner and continuing along the top border to the far right of the box. In contrast, the dashed 45 degree line illustrates the theoretical CAP curve for a perfectly random model where defaults are distributed proportionately across all scores. A curve lying farther to the "northwest" thus has greater discriminatory power than one lying closer to the 45 degree diagonal. Results may be ambiguous, however, when one curve crosses another.

To summarize the performance, or model power, reflected in a CAP curve, one can calculate an *Accuracy Ratio*. We define an Accuracy Ratio (AR) as the area lying between a given CAP curve and a 45 degree line, divided by the total area lying above the 45 degree line. As such, an AR is a statistic that reflects both Type I (false negative) and Type II (false positive) error. An AR of 100% would indicate that all defaulting issuers received the very lowest classification (assigning them the highest probability of default).

13. *For a description of bond-implied rating calculations, please see "Measuring the Performance of Corporate Bond Ratings," Moody's Special Comment, by Richard Cantor and Christopher Mann, April 2003.*

Table 2

One-Year Horizon Accuracy Ratios

1999 - 2003 Combined Sample					
Bond Implied Ratings	83.3%				
MDP Implied Ratings	76.0%				
Moody's Ratings	74.3%				
By Year	**1999**	**2000**	**2001**	**2002**	**2003**
Bond Implied Ratings	79.7%	73.8%	85.7%	88.5%	91.1%
MDP Implied Ratings	73.5%	64.7%	79.8%	77.2%	82.9%
Moody's Ratings	72.4%	59.4%	75.7%	80.9%	87.8%
AR(Bond Implied) - AR(MDP Implied)	6.3%	9.2%	5.9%	11.3%	8.1%
AR(Bond Implied) - AR(Moody's)	7.3%	14.4%	9.9%	7.5%	3.2%
AR(MDP Implied) - AR(Moody's)	1.0%	5.3%	4.0%	-3.7%	-4.9%

Table 2 shows AR statistics calculated for Bond implied ratings, MDP implied ratings, and Moody's ratings over the period 1999 – 2003. Note that the AR for MDP implied ratings generally lies between that for Bond implied ratings and Moody's ratings. In other words, over this time period and for the single task of predicting default probability over a one-year time horizon, Bond implied ratings were the most accurate, followed by MDP implied ratings, and closely followed by Moody's ratings. Bond implied ratings benefit, relative to MDP implied ratings, from the market's assimilation of information above and beyond financial ratio statistics.[14]

Also included in Table 2 are AR statistics for the three rating systems calculated over datasets for each year, 1999 through 2003. Unfortunately, it is difficult to compare accuracy ratios across different datasets as they are sensitive to the relative number of defaults and to the total number of observations in each dataset. An alternative method is to compare two rating classification systems relative to a third. This is done by taking the ARs of two systems for a dataset and subtracting from each the AR of a third system and comparing these differences across datasets. To this effect, Table 2 also shows the differences between the ARs of Bond implied ratings, MDP implied ratings, and Moody's ratings. In recent years, relative to Bond implied ratings, MDP implied ratings appear to have maintained fairly similar accuracy over time. Moody's ratings, however, have increased in accuracy over time relative to Bond implied ratings. This is further exhibited by the change in the difference between ARs of MDP implied ratings and Moody's ratings year-to-year. It would appear that since 2002, Moody's ratings have become more accurate than MDP implied ratings, but are still not as accurate as Bond implied ratings.

The higher accuracy of Bond implied ratings is not without cost. Market implied credit opinions are volatile, often changing full implied rating categories multiple times in a given year.[15] Table 3 highlights two important measures of ratings volatility, the percentage of issuers experiencing any rating change between quarters and the percentage of issuers with "large" rating changes (here defined as rating changes of three or more notches) between quarters, calculated over the combined 1999 – 2003 sample. Bond implied ratings are the most volatile measure, followed by MDP implied ratings, and finally Moody's ratings. Note that Bond implied ratings are substantially more volatile than Moody's ratings, and that the volatility of MDP implied ratings lies in between the two.

Table 3

Volatility Ratios

1999 - 2003 Combined Sample

	Issuers with Quarterly Rating Actions	Issuers with Large Quarterly Rating Actions
Bond Implied Ratings	62.2%	8.0%
MDP Implied Ratings	46.7%	6.7%
Moody's Ratings	9.0%	1.4%

14. *Cantor and Mann, ibid., have shown that the accuracy of Moody's ratings improves, relative to the accuracy of bond implied ratings, as the investment horizon is extended beyond one year. We too find that Moody's ratings are considerably more accurate than one-year MDP estimates at longer horizons. Furthermore, it is worth noting that the accuracy of Moody's ratings greatly improves at all horizons if one takes into account Rating Outlook and Watchlist designations. For more information, please see David Hamilton, and Richard Cantor, "Rating Transition and Default Rates Conditioned on Outlooks," Journal of Fixed Income, September 2004.*
15. *Please see Cantor and Mann, op cit.*

Implications for Fundamental Credit Analysis

The statistical model described above does not point the way to new or improved accounting ratios for use in fundamental credit analysis. Aside from the volatility measure, only ratios commonly used by financial analysts today were tested. But the model can provide important insight into the appropriate weight one should assign to each ratio.

Fundamental analysis is a framework for assessing creditworthiness. As one part of fundamental credit analysis, accounting ratios are computed and compared against benchmarks. Yet there is generally little guidance for situations in which a given entity ranks high along one accounting ratio measure and low along another. Does leverage dominate liquidity or coverage?

In cases where one is trying to predict a one-year default probability, interest coverage, as defined above, should receive the greatest emphasis. Where other measures provide ambiguous or conflicting guidance, interest coverage should dominate. Indeed, our testing found that a model containing only interest coverage is nearly 90% as accurate as the complete model. A model containing interest coverage and leverage together displays more than 95% of the accuracy of the complete model.

Summary

We introduced a one-year default prediction model for large non-financial firms. The model can serve as an important tool in the practice of fundamental credit analysis. The model described herein is capable of identifying significant predictors of future default risk. In particular, it validates the important role of interest coverage and leverage in determining default risk. Finally, its accuracy, while lower than a pure market measure of credit risk, is quite acceptable. Moreover, the lower output volatility of the model makes it useful in guiding credit decisions.

Appendix

Financial ratios tested for significance:

5-Year Net Income Volatility
5-Year Revenue Volatility
Adjusted Debt / Adjusted Capital
(Adjusted Debt – Receivables) / Adjusted Capital
Asset Growth
Cash and Equivalents
(Cash + Equivalents) / Assets
(Cash – Current Debt) / Assets
Current Debt / (Cash + Equivalents)
Current Ratio
Depreciation / Plant, Property and Equipment
EBIT / Interest Expense
(EBIT + 1/3 Rent) / [Interest Expense + 1/3 Rent + (Preferred Dividends / 0.65)]
EBITDA / Interest Expense
(EBITDA + 1/3 Rent) / Interest Expense
(EBITDA + Rent) / Interest Expense
(EBITDA – Change in Assets) / Total Debt
Gross Cash Flow / Total Debt
Inventories
Inventories / Total Assets
Liquidity Adjusted Debt / Liquidity Adjusted Capital
Net Income
Operating Profit / Revenue
Retained Cash Flow / Adjusted Debt
Retained Cash Flow / Gross Capital Expenditure
Retained Cash Flow / Total Debt
(Retained Cash Flow – Capital Expenditure) / Adjusted Debt
(Retained Cash Flow – Depreciation – Amortization) / Adjusted Debt
Retained Earnings
Retained Earnings / Assets
Return on Average Common Equity
Return on Average Assets
Return on Average Capital
Return on Equity
Revenue
Revenue Growth
Revenue / Assets
Total Debt / Total Book Capital
(Total Debt – Cash) / Assets
Total Assets
Total Debt / EBITDA
Total Equity
Total Equity / Debt

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