Applying Credit Score Models to Multiple States of Nature

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The financial literature offers several universal schemes for estimating corporate bankruptcy risk. Among the more popular approaches are the financial ratios model of Altman [1968], the alternative accounting ratios model proposed by Ohlson [1980], and the Cash Flow Based Model (CFBM) offered by Aziz, Emanuel, and Lawson [1988].

This study executes a comparative analysis of these methodologies in various states of nature, and offers an alternative model for each scenario. We further demonstrate how differences in predictive strength can lead to economically significant variations in portfolio performance. Most importantly, we investigate why differences arise in the predictive power of these three approaches.

There are some fundamental differences among the three models. Altman [1968] and Ohlson [1980] use different accounting ratios derived from the income statement and the balance sheet to capture the financial strength of a firm. Above all, the Altman Z-score relies upon operating income, while the Ohlson O-score utilizes net income—both scaled by total assets—to predict changes in creditworthiness. However, cash flow bankruptcy models suggest that insufficient cash available to service existing debt could trigger deterioration in creditworthiness; thus, the CFBM-score uses operating cash flow as its main indication for future variations in default odds.

In addition, the Altman Z-score and the CFBM-score are created through Multiple Discriminant Analysis (MDA), whereas the Ohlson O-score is generated through a Conditional Logit Model (CLM). These are two different statistical methods. The MDA maximizes the difference between values of the dependent variables that classify a group of bankrupt firms and a second group of survived firms. This technique requires similar variance-covariance matrices in both groups, as well as normally distributed predictors. The CLM examines how corporate distress characteristics affect the likelihood of bankruptcy filing. It uses a probabilistic estimation based on logistic regression over a joint pull of bankrupt and viable assets.

Yet, all these predictive techniques share an important characteristic. They all assign comparable quantitative measures to the chances of bankruptcy filing apart from the present business cycle and regardless of the current credit rating.

This study examines the predictive power of these common methodologies of credit risk within different states of nature, and investigates why some models perform better than others under different circumstances. For that, we construct four separate states by distinguishing between expansionary and contractionary business cycles, and by differentiating between investment and speculative credit ratings. In addition, we propose an alternative unique score for each of these states of nature, while conducting a comparative analysis of predictive strength and examining the economic importance of the discussed methodologies.

We are motivated to detect dissimilarities in the relative contribution of individual variables to the total predictive power of each credit score, and to explore the sources of this diversity. Our main contribution to the literature is by clarifying the foundations of diversity in predictive power of the three most commonly used credit scores; the Z-score, the O-score, and the CFBM-score. Not only do we spot dissimilarities in the performance of these three approaches when tested in different situations, but we also identify what causes this variation. We accomplish a secondary contribution by offering a unique alternative score constructed from a mixture of various accounting ratios for each of the examined states of nature.

Contrary to previous findings in the literature, throughout this research we discover that the Z-score achieves clear superiority over the other credit scores among the low rating grades, yet it performs just slightly better than average in most cases within high rating categories. When we compare its performance between business cycles, we detect slight improvement within weak market conditions over prosperous times. We further discover that the CFBM-score performs below average in most states of nature. The O-score has the worst predictive strength; however, it is highly valuable for relatively safe firms and when business conditions are thriving. The alternative proposed scores challenge the other credit scores in many of the examined states.

We further realize that the reasons for this diversity in predictive power among the credit scores are the conceptual accounting ratios used to construct them. In particular, EBIT over total assets is a central component of the Z-score, and it performs exceptionally well in most cases for predicting default. Net income scaled by total assets is a key part of the O-score, but it does not properly predict default except in superb market and firm conditions. This is possibly due to biases resulting from depreciation and amortization, interest expenses, and taxes. Operating cash flow divided by total assets is a principal component of the CFBM-score, and it achieves fairly good predictive strength across a range of different scenarios.

The research proceeds as follows. The next section reviews relevant prior studies, the third section discusses the data sample and presents the empirical methodologies, and the fourth section summarizes the results. The last section concludes.

BANKRUPTCY PREDICTION IN THE LITERATURE

This section first reviews prior literature on the relations between bankruptcy risk and business cycles, then summarizes some of the articles that explore the predictive strength of different credit models for various bond yields.

Numerous scholars examine the relation between default rates and the business cycle. Fama and French [1989] discover that short- and long-term business conditions, captured in the term spread, dividend yield, and default spread, are significant variables in the prediction of stock and bond returns. Alessandrini [1999] empirically examines how interest rate risk and credit risk are associated with the stage of business cycle. Using monthly observations from 1954 to 1997 on the U.S. market, the author finds that credit spreads are sensitive to recessionary and expansionary periods, with a stronger effect during recessions and among lower-rated bonds. Bangia, Diebold, Kronimus, Schagen, and Schuermann [2002] condition transition matrices on stochastic business cycles, and realize that distinguishing between expansionary and recessionary periods leads to a significant reduction in the level of uncertainty over long-term horizons.

Several studies test the prediction of default among low- and high-yield bonds. Altman [1989] and Asquith, Mullins, and Wolff [1989] detect a positive correlation between the amount of time high-yield bonds are outstanding and their chances of default. Huffman and Ward [1996] investigate four common methodologies which predict default at the time of issuance of high-yield bonds. The authors report that bankruptcies of high-yield issues are often related to higher growth rates, lower operating profit margins, more collateralized assets, and higher variability in working capital. Marchesini, Perdue, and Bryan [2004] reveal the inability of four universal bankruptcy prediction approaches to forecast default of high-yield bonds with no better than a 61.5% accuracy rate. The authors conclude that firms issuing high-yield bonds are often associated with having poor accounting ratios, and perhaps these skewed variables reduce the predictive power.

SAMPLE AND METHODOLOGIES

Data

We obtain 20 years of data, from 1986 to 2005, from several sources: Compustat, the National Bureau of

Economic Research (NBER) website, the Conference Board website, and the Bureau of Economic Analysis (BEA) website.

To compute the firms' Altman Z-scores, we used data supplied by Compustat for current assets, current liabilities, total assets, total liabilities, net sales, retained earnings, EBITDA, depreciation and amortization, equity closing prices, and common shares outstanding. To estimate the Ohlson O-scores, Compustat data was also used for information regarding current liabilities, current assets, and net income. To compute the CFBM-scores, the Compustat database was again used to access operating cash flow, capital investment, taxes, cash and marketable securities, interest payments, and short-, medium-, and long-term debt.

Furthermore, Compustat provides Standard & Poor's (S&P) long-term domestic issuer credit ratings. Credit categories numbered 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, and 27 are considered valid. The credit score 2 represents the highest possible credit rating (AAA), the credit score 14 indicates the highest category classified as speculative grade (BB), and the credit score 27 denotes filing for bankruptcy. Higher credit scores denote lower credit ratings or deterioration in the creditworthiness of a firm.

The NBER distinguishes between various business cycles by identifying certain months as being in an expansionary or contractionary stage. This identification is determined by examining a large number of business indicators and may reflect improving or deteriorating business conditions.

Our second division of business segments involves the Consumer Confidence Index (CCI). This index is maintained by the Conference Board, an independent non-profitable organization, and is almost identical to the Consumer Sentiment Index of the University of Michigan.[1] It is derived from a survey of 5,000 households and may point to shifts in consumption patterns and, thus, a progression in business cycles. The percentage change in the CCI for each consecutive month is calculated and then accumulated for each quarter. Positive and negative quarterly percentage changes in the CCI are identified and used to separate between positive and negative business segments.

The Bureau of Economic Analysis (BEA), an agency of the U.S. Department of Commerce, provides quarterly GDP growth rates. These records assist in the computation of the Ohlson O-score.

Methodologies

From the initial data sample, we eliminate firms in the financial service industries, firms with problematic values, and any observations that are missing vital data. After collecting information concerning the creditworthiness of various firms, we compute for each of the remaining observations the three most commonly used credit risk scores—the Z-score, the O-score, and the CFBM-score—illustrated hereafter.

Altman [1968] uses multiple discriminant analysis to combine a set of five financial ratios into a single measure called the Z-score. This quantity aims to predict a public company's likelihood of default. The Altman Z-Score is computed as follows:

$$\begin{aligned}\text{Z-Score} = {} & 3.3\ (\text{EBIT/Total Assets}) + 0.999\ (\text{Net Sales/}\\ & \text{Total Assets}) + 0.6\ (\text{Market Value of Equity/}\\ & \text{Total Liabilities}) + 1.2\ (\text{Working Capital/Total}\\ & \text{Assets}) + 1.4\ (\text{Retained Earnings/Total Assets})\end{aligned} \tag{1}$$

where a lower Z-score denotes a higher likelihood of default, and vice versa. We further calculate for each observation the original Ohlson [1980] O-score.[2] The O-score, as a measure of the likelihood of bankruptcy, is computed as follows:

$$\begin{aligned}\text{O-score} = {} & -2.63 - 0.267\ [\log(\text{Total Assets/GDP Price}\\ & \text{Level Index})] + 5.63\ (\text{Total Liabilities/Total}\\ & \text{Assets}) - 1.43\ (\text{Working Capital/Total Assets})\\ & + 0.0585\ (\text{Current Liabilities/Current Assets})\\ & - 2.35\ (\text{Net Income/Total Assets}) - 1.99\\ & (\text{Funds provided by Operations/Total Liabilities}) + 0.307\ (1 \text{ if Net Income is Negative for}\\ & \text{the Past Two Years, 0 Elsewhere}) - 1.56\ (1 \text{ if}\\ & \text{Total Liabilities} > \text{Total Assets, 0 Elsewhere})\\ & - 0.5092\ [(\text{Net Income}_t - \text{Net Income}_{t-1})/\\ & (|\text{Net Income}_t| + |\text{Net Income}_{t-1}|)]\end{aligned} \tag{2}$$

where an increase in the O-score denotes deterioration in a firm's creditworthiness and a decrease in the O-score suggests improvement in a firm's credit risk.

The CFBM-score for assessing bankruptcy risk is computed in the manner of Aziz, Emanuel, and Lawson [1988], as follows:[3]

$$\text{CFBM} = 3.007 - 6.601\ (\text{Operating Cash Flow/Total Assets}) - 5.183\ (\text{Capital Investment/Total Assets}) - 32.200\ (\text{Taxes/Total Assets}) + 5.823\ (\text{Liquidity Change/Total Assets}) - 121.44\ [(\text{Interest Payments} - \text{Short, Medium, and Long Term Debt})/\text{Total Assets}] \quad (3)$$

where *Liquidity Change* denotes changes in cash and marketable securities over the previous quarter. In general, a higher CFBM-score means a worsening in the creditworthiness of a firm, and vice versa.

We then categorize each observation by the proper state of nature with respect to its business cycle and its credit rating. A business cycle is defined first as being in an expansionary or contractionary stage based on the NBER classification. For purposes of robustness, we also distinguish between positive and negative business segments based on the sign (+/–) of the quarterly percentage change in the CCI.

We further classify as a "high" credit rating those observations identified as having a credit score of 2, 4, 5, 6, 7, 8, 9, 10, 11, 12, and 13, and as a "low" credit rating those observations having a credit score of 14, 15, 16, 17, 18, 19, 20, 21, 23, 24, and 27. Each group contains the same number of credit grades with the demarcation set at the credit score of 14 (BB), the highest category classified as non-investment grade.

To examine the predictive strength of the different models, in the two years prior to bankruptcy filing we classify observations as "defaulted" firms. We then create for each subsample within the different states of nature a matching control group containing "non-defaulted" firms. The defaulted and non-defaulted firms are matched based on their industry group and with respect to firm size. We eliminate deviations larger than 20% above or below the defaulted firm's total assets.

In total, we segregate the sample into four subsamples twice; first, by considering expansionary and contractionary business cycles based on the NBER definition and, second, by the sign of percentage change in the CCI; in each instance, the S&P credit ratings are used as a second classifier.

In all these states of nature, we define 15 credit-related accounting ratios. We present the ratios, their significance to default prediction as derived from an independent two-sample t-test, their method of computation, and their relevancy to different credit scores in Exhibit 1. Some of these ratios will later assist in explaining the differences in predictive power among the various models. To avoid over-classification and to prevent the use of redundant variables, we intentionally exclude a few of the ratios and conditions that appear in the traditional credit scores while we add two pertinent ratios—cash and short-term investment over sales, and market-to-book value as a proxy for the growth rate.

To form a distinctive credit score for each of the states of nature, we execute a Canonical Discriminant Analysis (CDA) based on these 15 accounting ratios. The CDA determines the most parsimonious way to distinguish between equal- or unequal-size classes (defaulted and non-defaulted firms) by deriving a linear combination of the discriminant variables (the 15 accounting ratios) that has the highest possible multiple correlation with those classes, and by allocating appropriate canonical weights to the independent variables that separate the classes most effectively.[4]

Once we obtain the four different scores—the Z-score, O-score, CFBM-score, and CDA-score—for each observation within all states of nature, we scale them into comparable default probabilities according to the following procedure. We count and rank the different scores in consecutive order within each state of nature so that the highest score is ranked as one, the second highest score is ranked as two, and so forth. Because a lower Z-score means higher default probability, we scale it by dividing its rank by the total number of Z-scores. Since a higher O-score, CFBM-score, and CDA-score mean higher default probabilities, we scale them by dividing the number of scores plus one minus the rank by the number of the corresponding scores. In this way, we map the scores into a (0, 1) domain and capture the equivalent default probabilities.

We then contrast the predictive strength of these default probabilities using a receiver operating characteristics (ROC) curve methodology. The ROC of a classifier shows its performance as a trade-off between type-I and type-II errors.[5] A type-I error relates to failing to identify a default in advance, or to assigning a lower default probability than a fixed cutoff point. A type-II error relates to preliminarily misidentifying a non-default firm as a

EXHIBIT 1

Variables Tested in Canonical Discriminant Analyses (CDA)

Accounting Ratio	Two-Sample t-Test Values	Way of Computation	Appears in...
EBITASSETS [A]	9.700 ***	EBIT/Total Assets	Z-Score
SALESASSETS	2.335 **	Net Sales/Total Assets	Z-Score
EQUITYDEBT	9.913 ***	Market Value of Equity/Total Liabilities	Z-Score
WORKASSETS	4.812 ***	Working Capital/Total Assets	Z-Score, O-Score
RETASSETS	17.251 ***	Retained Earnings/Total Assets	Z-Score
ASSETSGDP	3.986 ***	log of (Total Assets/GDP)	O-Score
DEBTASSETS	12.682 ***	Total Liabilities/Total Assets	O-Score
CURDCURA	0.612	Current Liabilities/Current Assets	O-Score
NIASSETS [A]	8.626 ***	Net Income/Total Assets	O-Score
FUNDSDEBT	5.639 ***	Funds by Operations/Total Liabilities	O-Score
CFASSETS [A]	4.576 ***	Operating Cash Flow/Total Assets	CFBM-Score
CAPASSETS	16.538 ***	Capital Investment/Total Assets	CFBM-Score
TAXASSETS	6.770 ***	Taxes/Total Assets	CFBM-Score
CASHSALES [B]	5.124 ***	Cash and Short Term Investment/Sales	General Ratio
GROWTHRATE [B]	9.277 ***	Market-to-Book Value	General Ratio

*The exhibit presents 15 credit-related accounting ratios, their significance to default prediction, method of computation, and relevancy to different credit scores in the financial literature. These variables construct the CDA in the various states of nature. The ratios EBITASSETS, NIASSETS, and CFASSETS are later used to rationalize the differences in predictive strength among the Z-score, O-score, and CFBM-score. The ratios CASHSALES and GROWTHRATE do not appear in the traditional scores, but they are considered relevant to corporate creditworthiness. The importance of these two variables is examined in several studies including De Bondt and Thaler [1987]; Fama and French [1992]; Huffman and Ward [1996], and Marchesini, Perdue, and Bryan [2004]. To authenticate the individual discriminating ability of these 15 accounting ratios, the two subsamples of defaulted and non-defaulted firms are compared and analyzed using an independent two-sample t-test. The corresponding t-values appear in the second column, where ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level or better, respectively, when examined with infinite degrees of freedom.*

default candidate, or to assigning a higher default probability than the fixed cutoff point. Minimizing one type of error often comes at the expense of increasing the other.

To avoid contrasting the models using only one predetermined cutoff point, typically an ROC curve is plotted with the false-positive rate on the horizontal axis and the true-positive rate on the vertical axis, while the cutoff point is allowed to vary. In this way, the probabilities of type-II errors are plotted against one minus the probabilities of type-I errors. The ROC curve always goes through the two points (0, 0) and (1, 1). The point (0, 0) classifies all cases as non-default, hence the classifier discovers all the negative cases, but finds no positives. The point (1, 1) classifies all cases as positive, hence all default cases are correctly predicted, but all non-default cases are mistakenly identified. A classifier with random guesses will have an ROC curve along the diagonal between these two points where a better predictive power will result in an ROC curve closer to the northwest corner. When the locus of points generating the ROC curve is closer to the (0, 1) corner, the model has less type-I errors or less type-II errors, hence a higher predictive strength.

We also assess the economic importance of the differences in predictive power in the different states of nature. For that, we perform lending simulations using the previously discussed power analysis. This investigation illustrates the economic consequences of making lending decisions based on each model in each state of nature.

Our setting describes a genuine scenario where lenders measure the borrowers' creditworthiness and charge monotonically increasing interest rate payments with respect to default likelihoods. All lenders calculate the Z-score, O-score, CFBM-score, and CDA-score, then scale them into comparable default probabilities and make independent lending decisions in each state of nature. If the cutoff-based lending point falls below the default probability, the borrower is not granted credit, and the lender takes neither profits nor losses. If however, the cutoff-based lending point is higher than the default probability, the loan is accredited and further profits or losses are expected.

We make the simplifying assumptions that all firms seek loans in the same amount of $1 million and for the same time horizon of one year. If a loan transaction matures prior to default, the lender receives its predetermined interest rate charges as a profit. However, if the default event occurs before the end of the lending year, the lender bears a loss of $1 million minus the recovery rate (RR).[6] Underwriting fees are presumed to be constant and equal for all transactions, and hence can be ignored.

We consider that lenders allow interest rate charges to vary with respect to default risk, thus they assign the borrower a cost function of (4 + 16 * Default Probability)%. This way, interest rate payments are near 4% for the high credit quality firms, and may reach up to 20% for the riskier ones.

A profitable lending transaction occurs when the cutoff-based lending point is above the default probability and the borrower does not default prior to loan maturity. Therefore, the probability of a profitable lending transaction is the complement of a type-II error. A costly lending transaction occurs when the cutoff-based lending point is above the default probability and the borrower defaults prior to the loan expiration date. Thus, the likelihood of a costly lending transaction is the type-I error probability.

The total lenders' expected profit/loss profiles are estimated for the different models. These profiles are compared over 21 different portfolios constructed from 21 different cutoff-points on the ROC curves. The first portfolio is composed using a cutoff-based lending point of 1.0, thus in this portfolio loans are given to all possible borrowers. The last portfolio is composed using a cutoff-based lending point of 0.0, so that loans are not granted to any of the firms and, thus, no profits or losses are expected.

At last, we would like to explore why some models perform better than others in different states of nature. We, therefore, authenticate the relevancy of accounting ratios to default while examined under different credit categories and within different business cycles. We are particularly interested in discovering the applicability of three ratios—*EBIT over total assets* from the Z-score, *net income over total assets* from the O-score, and *operating cash flow over total assets* from the CFBM-score.[7]

After labeling the rating classes and the business cycles, we merge all sub-samples, and create interaction terms between the three accounting ratios and the credit rating classes, as well as the business segments. To eliminate the possibility of multicollinearity, we conduct a correlation analysis of the explanatory variables and deploy three separate regressions as follows:

$$\begin{aligned}\text{Default} = \alpha + \beta_1\left(\text{RC}\times\frac{\text{EBIT}}{\text{TA}}\right) + \beta_2\left(\text{RC}\times\frac{\text{NI}}{\text{TA}}\right)\\ +\beta_3\left(\text{RC}\times\frac{\text{CF}}{\text{TA}}\right)+\varepsilon\end{aligned} \tag{4}$$

$$\begin{aligned}\text{Default} = \delta + \gamma_1\left(\text{BC}\times\frac{\text{EBIT}}{\text{TA}}\right) + \gamma_2\left(\text{BC}\times\frac{\text{NI}}{\text{TA}}\right)\\ +\gamma_3\left(\text{BC}\times\frac{\text{CF}}{\text{TA}}\right)+\omega\end{aligned} \tag{5}$$

$$\begin{aligned}\text{Default} = \lambda + \eta_1\left(\text{RC}\times\text{BC}\times\frac{\text{EBIT}}{\text{TA}}\right)\\ +\eta_2\left(\text{RC}\times\text{BC}\times\frac{\text{NI}}{\text{TA}}\right)\\ +\eta_3\left(\text{RC}\times\text{BC}\times\frac{\text{CF}}{\text{TA}}\right)+\varphi\end{aligned} \tag{6}$$

where RC = Rating Class, BC = Business Cycles,

$$\text{Default} = \begin{cases} 0 & \text{No Default Occurs during the Following Two Years} \\ 1 & \text{Default Occurs during the Following Two Years} \end{cases}$$

$$\text{RC} = \begin{cases} 1 & \text{High Credit Ratings (2, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13 Scores)} \\ 2 & \text{Low Credit Ratings (14, 15, 16, 17, 18, 19, 20, 21, 23, 24, 27 Scores)} \end{cases}$$

$$\text{BC} = \begin{cases} 1 & \text{Expansionary Business Cycle (NBER) or Positive }\%\Delta\text{ in CCI} \\ 2 & \text{Contractionary Business Cycle (NBER) or Negative }\%\Delta\text{ in CCI} \end{cases}$$

The notations α, δ, and λ signify the intercepts of the regressions; β_i, γ_i, and η_i denote the coefficients of the examined interaction terms; and ε, ω, and ϕ are the error terms assumed to be normally distributed.

Descriptive Information

Our final sample contains 1,463 firm-year observations with the following distribution: 1987 (3), 1988 (22), 1989 (47), 1990 (27), 1991 (36), 1992 (52), 1993 (71), 1994 (55), 1995 (49), 1996 (84), 1997 (101), 1998 (111), 1999 (150), 2000 (124), 2001 (44), 2002 (137), 2003 (131), 2004 (112), and 2005 (107).

These public firms spread along 16 industry groups as follows: agricultural (11); products and mining (86); oil and gas (107); machinery and construction (1); food and beverages (19); textiles and clothing (43); wood products (46); books and publishing (5); chemical products (140); medical and pharmaceuticals (50); vehicles, aircrafts, and ships (21); electronics (61); communications and telecommunications (42); transportation services (69); retail stores (332); and others (430).

We provide brief summary statistics on the variables involved in this research in Exhibit 2. The final sample varies from exceptionally safe to highly risky firms, as expressed by all bankruptcy risk measurements. Furthermore, all 15 accounting ratios diverge between fairly low, and sometimes even negative, estimations to high values.

After carefully reviewing the firm-year distribution, the industry-group allocation, the dispersal of the bankruptcy risk quantities, and the dissemination of the accounting ratios, we conclude that potential sample selection errors are kept to a minimum level.

EMPIRICAL RESULTS

This section discusses the main findings of the research. Exhibit 3 presents brief summary statistics on the total number of firms in our samples the number of defaulted firms, and the number of matching non-defaulted firms in each state of nature, as well as displays a comparative performance evaluation of the four examined credit scores—the Z-score, O-score, CFBM-score, and CDA-score—in each state of nature, sorted from the best-performing to the worst-performing model. The comparison is made through a comparative analysis of the corresponding ROC curves with the following decision rules:[8] 1) when there is an obvious distinction between the curves, the higher curve is clearly considered as preferable; and 2) when two curves intersect each other, the better performing model is defined based on the most profitable cutoff-based lending point with a fixed RR of 0.2.

Panel A shows the results within the four states of nature constructed from the NBER definition of business cycles and the separation of high- and low-credit ratings by S&P. Panel B reveals the findings within four different states of nature assembled from the sign of percentage change in the CCI and the partition of high- and low-credit ratings by S&P.

We find that the Z-score performs exceedingly well in all states of nature. In both simulations, the Z-score achieves clear superiority over the other credit scores among the low rating grades, yet it performs only better than average in most cases within the high rating class.[9] In addition, when comparing its performance between the business cycles, we detect minor improvement within the contractionary stage over the expansionary stage, and within the negative changes in CCI over the positive changes in CCI. We thus suspect that the relation between the accounting components used in constructing the Z-score—EBIT over total assets, in particular—and the default likelihoods rely upon current credit rating and present business conditions.

We further discover that the CFBM-score performs below average in most states of nature in the two simulations, except for the positive business segment defined by the percentage changes in CCI. We find little evidence for dissimilarities in the CFBM-score performance between the low- and high-rating classes, with merely a minor improvement among the low-quality over the high-quality categories in the second simulation. We deduce that the relation between cash flow components within the CFBM-score and default odds depends neither on rating class, nor business segment.

We also find that when compared to other credit scores, the O-score performs very poorly in most states of nature except for two cases—1) the expansion business cycle by NBER and high credit ratings, and 2) the positive percentage changes in CCI and high credit ratings. It appears that the O-score is valuable only among relatively safe firms, and solely in prosperous business conditions. We presume that the net income scaled by total assets ratio—a central accounting module in the O-score—is a viable predictor of defaults for firms having selected credit rating categories, and only in specific business cycles.

The CDA-score provides proper alternative risk assessment methodology to the other examined credit scores. We intentionally construct the CDA-score using a blend of accounting ratios from the other three credit scores, while trying to avoid over-classification. When

EXHIBIT 2
Descriptive Statistics

Variable	Mean	St. Dev.	Median	Minimum	Maximum
Bankruptcy Risk Measures					
Altman Z-Score	1.22	0.61	1.15	0.00	4.81
Ohlson O-Score	0.77	0.65	0.63	0.00	4.10
CFBM-Score	7.09	1.58	6.92	2.62	14.54
CDA-Score	-0.26	0.82	-0.05	-4.97	6.36
S&P Credit Ratings	14.64	3.98	14 (BB)	5 (AA)	27 (D)
Accounting Ratios					
EBITASSETS	0.02	0.02	0.02	-0.06	0.12
SALESASSETS	0.34	0.25	0.26	0.01	1.45
EQUITYDEBT	0.84	0.70	0.68	0.00	6.43
WORKASSETS	0.09	0.12	0.08	-0.40	0.60
RETASSETS	0.13	0.15	0.12	-0.83	0.90
ASSETSGDP	1.52	0.91	1.43	-1.08	5.50
DEBTASSETS	0.75	0.13	0.73	0.49	1.46
CURDCURA	0.85	0.48	0.73	0.08	4.23
NIASSETS	0.01	0.03	0.01	-0.70	0.69
FUNDSDEBT	0.07	0.06	0.06	-0.15	0.43
CFASSETS	0.05	0.05	0.05	-0.14	0.35
CAPASSETS	0.67	0.19	0.71	-0.22	0.96
TAXASSETS	0.01	0.01	0.01	-0.07	0.06
CASHSALES	0.27	0.44	0.11	0.00	5.00
GROWTHRATE	0.61	0.53	0.49	0.00	6.14

The exhibit provides summary statistics of the test variables for a sample of 1,463 observations from 1986 to 2005. For each variable, we describe the mean, standard deviation, median, lowest quantity, and highest value measured. We present this information for the bankruptcy risk measurement—the Z-score, O-score, CFBM-score, CDA-score—and the S&P credit rating analysis, as well as for the 15 credit-related accounting ratios.

compared to the other scores, the CDA-score performs slightly better in contraction cycles than in expansion cycles, and within the negative over the positive percentage changes in CCI. This substitute score achieves the best performance in the second simulation among high credit ratings, and it challenges the other scores in most of the remaining states of nature.

We present the weights of the CDA in the different states of nature in Exhibit 4. The 15 examined accounting ratios are listed in the first column and the canonical weights are presented in the second and third columns.

A selected sample of the ROC curves in various states of nature along with the corresponding profit/loss profiles are illustrated in Exhibits 5 and 6. These charts demonstrate the differences in predictive power between the four credit scores as well as the economic meanings of these variations. Exhibit 5, Panel A, reveals that for the NBER-defined expansionary business cycle and low S&P credit categories state, the Z-score displays the highest predictive power, the CDA-score the second highest, the CFBM-score the third highest, and the O-score the least predictive power. Exhibit 5, Panel B, illustrates that the slight difference in the models' predictive power leads to economically significant differences in portfolio performance. For example, at the most profitable cutoff-based lending points, when RR equals 0.4, the Z-score generates a profit to the lender of $66.405 million, the CDA-score a profit of $62.706 million, the CFBM-score a profit of $59.921 million, and the O-score a profit of only $56.972 million.

Exhibit 6, Panel A, shows that for the negative changes in CCI and low S&P credit ratings state, the Z-score is the best performing model most of the time, the CDA-score has the greatest predictive strength only

EXHIBIT 3

States of Nature—General Information and Comparative Performance of Models

Panel A	High Credit Rating	Low Credit Rating
Expansionary Business Cycle by the NBER	Total No. of Firms: 3,573 No. of Defaulted Firms: 13 No. of Non-Defaulted Firms: 339 Performance of Models (from Best to Worst): O-score, Z-score, CDA-score, CFBM-score	Total No. of Firms: 2,199 No. of Defaulted Firms: 119 No. of Non-Defaulted Firms: 932 Performance of Models (from Best to Worst): Z-score, CDA-score, CFBM-score, O-score
Contractionary Business Cycle by the NBER	Total No. of Firms: 515 No. of Defaulted Firms: 4 No. of Non-Defaulted Firms: 11 Performance of Models (from Best to Worst): Z-score, CDA-score, CFBM-score, O-score	Total No. of Firms: 284 No. of Defaulted Firms: 23 No. of Non-Defaulted Firms: 24 Performance of Models (from Best to Worst): Z-score, CDA-score, CFBM-score, O-score
Panel B	**High Credit Rating**	**Low Credit Rating**
Positive Business Segment by the % Δ of CCI	Total No. of Firms: 2,388 No. of Defaulted Firms: 13 No. of Non-Defaulted Firms: 226 Performance of Models (from Best to Worst): CFBM-score, O-score, Z-score, CDA-score	Total No. of Firms: 1,377 No. of Defaulted Firms: 77 No. of Non-Defaulted Firms: 589 Performance of Models (from Best to Worst): Z-score, CFBM-score, CDA-score, O-score
Negative Business Segment by the % Δ of CCI	Total No. of Firms: 1,880 No. of Defaulted Firms: 4 No. of Non-Defaulted Firms: 44 Performance of Models (from Best to Worst): CDA-score, Z-score, CFBM-score, O-score	Total No. of Firms: 1,106 No. of Defaulted Firms: 65 No. of Non-Defaulted Firms: 345 Performance of Models (from Best to Worst): Z-score, CDA-score, CFBM-score, O-score

The exhibit presents additional information on the total number of firms in the subsamples, the number of defaulted firms, and the number of matching non-defaulted firms in each state of nature. The exhibits also display a comparative performance evaluation of the four examined credit scores—the Z-score, O-score, CFBM-score, and CDA-score in each state of nature, sorted from the best-performing to the worst-performing model. The comparison is made through a comparative analysis of the corresponding ROC curves. Panel A shows the results within the four states constructed from the NBER definition of business cycles and the separation of high- and low-credit ratings by S&P. Panel B reveals the findings within the four states assembled from the sign of percentage changes in the CCI and the partition of high and low S&P credit ratings.

occasionally, the CFBM-score places third, and the O-score ranks last. Exhibit 6, Panel B, demonstrates the attainable excess return to lenders due to improved predictive strength. For example, at the optimal cutoff-based lending points, when RR equals 0.6, the CDA-score yields a profit to the lender of $26.521 million, the Z-score a profit of $26.382 million, the CFBM-score a profit of $23.599 million, and the O-score a profit of $21.626 million.

We, therefore, conclude that even slight differences in predictive strength among the various scores lead to economically significant differences in portfolio performance. Lenders ought to utilize the finest possible model in each state of nature to achieve the highest portfolio performance.

Exhibit 7 portrays the results of the ratios' relevancy analysis. Panel A depicts the findings regarding the interactions between credit rating classes and the three accounting ratios in Equation (4). Panel B describes the findings concerning the interactions between business cycles and the three accounting ratios in Equation (5). Panel C presents the findings for the interactions between credit rating classes, business segments, and the three accounting ratios in Equation (6).

EXHIBIT 4
Canonical Discriminant Analyses (CDA) Results

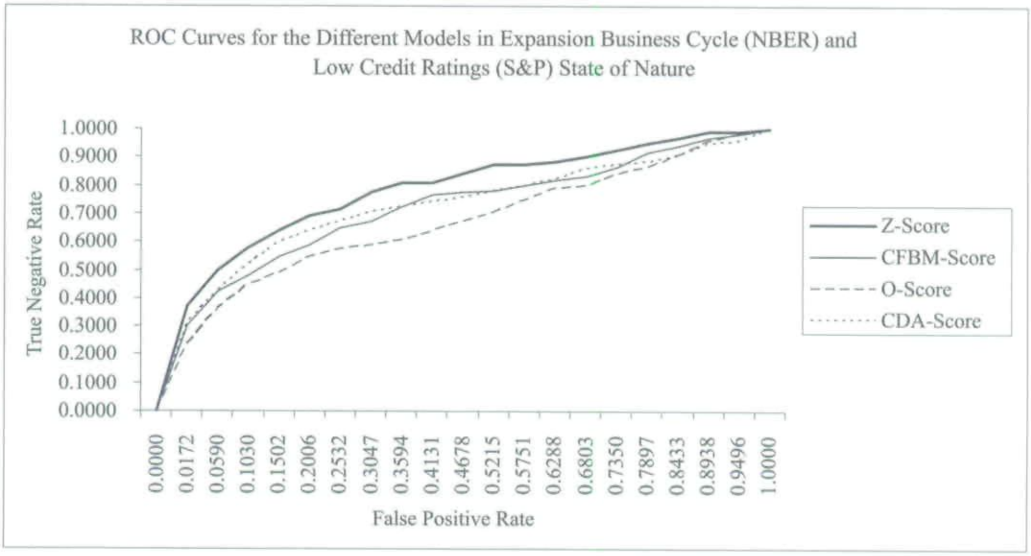
Panel A	Accounting Ratio	High Credit Rating	Low Credit Rating
Expansionary Business Cycle by the NBER	EBITASSETS	-0.605	0.259
	SALESASSETS	0.533	0.173
	EQUITYDEBT	-1.085	-0.814
	WORKASSETS	0.796	-0.219
	RETASSETS	0.448	0.550
	ASSETSGDP	-0.503	0.332
	DEBTASSETS	-0.433	-0.522
	CURDCURA	-0.173	-0.365
	NIASSETS	-0.057	-0.036
	FUNDSDEBT	-1.619	-0.735
	CFASSETS	1.901	0.717
	CAPASSETS	0.370	0.482
	TAXASSETS	-0.121	-0.036
	CASHSALES	0.182	-0.155
	GROWTHRATE	1.397	1.023
Contractionary Business Cycle by the NBER	EBITASSETS	2.355	-0.177
	SALESASSETS	-7.972	0.621
	EQUITYDEBT	0.518	1.529
	WORKASSETS	9.645	-0.403
	RETASSETS	-4.348	0.416
	ASSETSGDP	0.276	0.147
	DEBTASSETS	-3.987	0.976
	CURDCURA	4.277	-1.002
	NIASSETS	3.872	0.841
	FUNDSDEBT	-24.375	0.108
	CFASSETS	25.048	0.639
	CAPASSETS	-4.189	1.712
	TAXASSETS	-1.455	-0.345
	CASHSALES	-0.038	-0.688
	GROWTHRATE	0.000	-0.551
Panel B	**Accounting Ratio**	**High Credit Rating**	**Low Credit Rating**
Positive Business Segment by the % Δ of CCI	EBITASSETS	0.916	0.316
	SALESASSETS	0.381	0.271
	EQUITYDEBT	-1.143	-0.948
	WORKASSETS	-0.586	-0.190
	RETASSETS	0.429	0.357
	ASSETSGDP	-0.257	0.271
	DEBTASSETS	-0.790	-0.522
	CURDCURA	-0.081	-0.203
	NIASSETS	0.009	0.204
	FUNDSDEBT	-3.183	-0.598
	CFASSETS	3.554	0.587
	CAPASSETS	0.343	0.608
	TAXASSETS	-0.177	-0.174
	CASHSALES	0.168	-0.181
	GROWTHRATE	1.788	1.132
Negative Business Segment by the % Δ of CCI	EBITASSETS	-0.221	0.211
	SALESASSETS	0.849	0.241
	EQUITYDEBT	-12.499	-0.081
	WORKASSETS	-0.629	-0.066
	RETASSETS	1.389	0.722
	ASSETSGDP	-1.209	0.309
	DEBTASSETS	-0.074	-0.149
	CURDCURA	0.246	-0.285
	NIASSETS	1.332	-0.096
	FUNDSDEBT	4.633	-0.793
	CFASSETS	-4.148	0.813
	CAPASSETS	0.899	0.539
	TAXASSETS	-1.542	-0.074
	CASHSALES	0.136	-0.116
	GROWTHRATE	12.586	0.423

The exhibit presents the CDA weights attached to the 15 credit-related accounting ratios. Panel A reveals the results within the four states of nature created by the NBER definition of business cycles and the separation of high and low S&P credit ratings. Panel B shows the findings for the four states constructed by the sign of percentage changes in the CCI and the division of high and low S&P credit ratings.

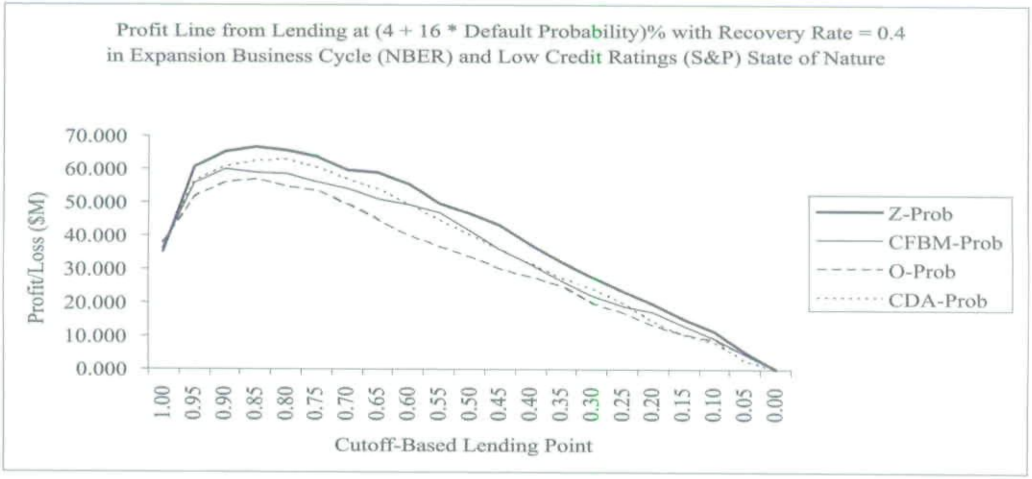
EXHIBIT 5

ROC Curves and Economic Significance for the Different Models—First Example

Panel A



Panel B



These exhibits illustrate the differences in predictive strength between the examined credit scores based on ROC curve comparative analysis, and highlight the economic importance of such diversity with a lending simulation.

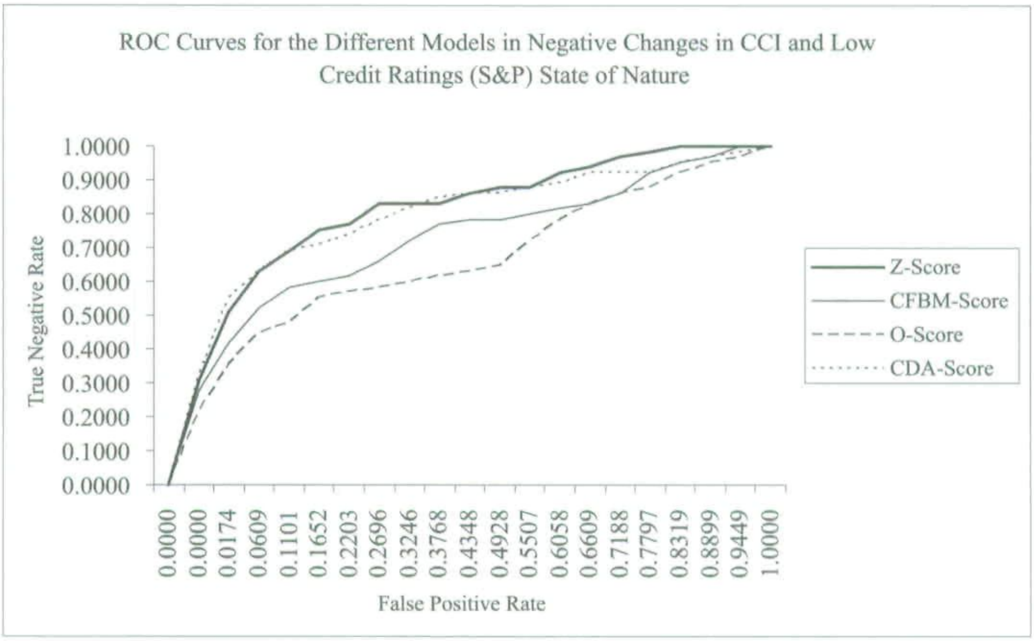
Each panel contains two parts. The first part designates the simulation derived from the expansionary versus contractionary business cycles defined by the NBER, and the second part represents the complement simulation obtained from the sign of percentage changes in the CCI. Within each part, we present the tested variables, the corresponding coefficients and their statistical significance, R-square, adjusted R-square, F-value signifying the significance of the regression model, and the variance inflation factor as an indication for multicollinearity.[10]

In Panel A we find strong evidence for a significant association between the two ratios—*EBIT over total assets* and *net income scaled by total assets*—and defaulted firms, conditional on the current rating class. In both simulations, we detect statistically significant relations between these two accounting ratios and the rating class as independent variables, and the state of default as dependent variable. We find no association between the interaction term containing *cash flow divided by total assets* and rating class, and between defaulted firms. We thus conclude that EBIT

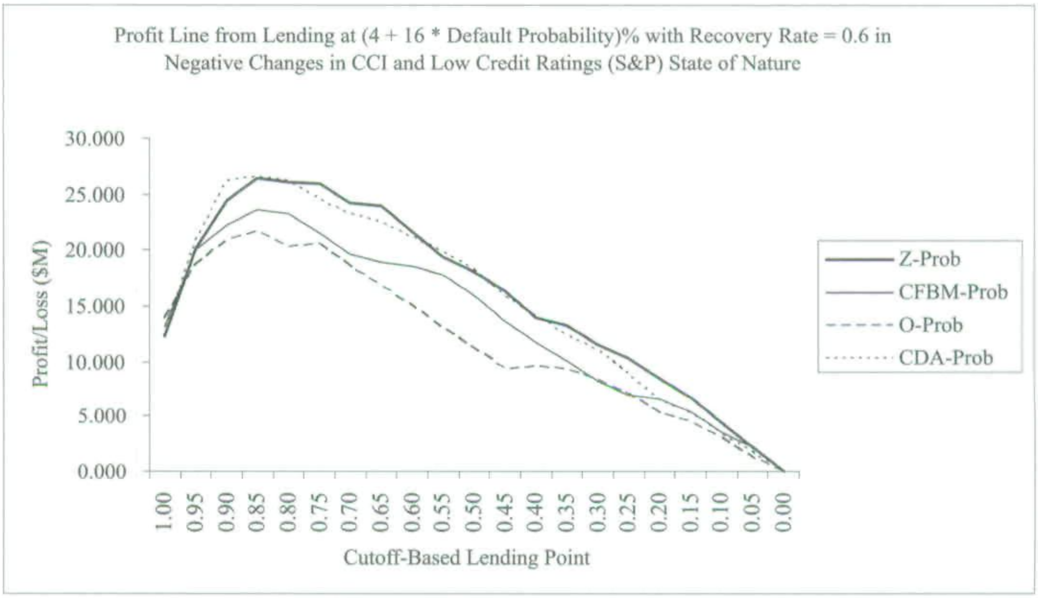
EXHIBIT 6

ROC Curves and Economic Significance for the Different Models—Second Example

Panel A



Panel B



These two exhibits illustrate the differences in predictive strength between the examined credit scores based on ROC curve comparative analysis, and highlight the economic importance of such diversity with a lending simulation.

and net income affect default likelihoods with reliance on the present credit rating class.

In Panel B we observe similar dependencies, only this time the interaction terms define reliance on the business cycle. In both simulations, *EBIT over total assets* and *net income over total assets* exhibit a robust relation to default odds with a clear association to existing business segments, while the interaction between *cash flow scaled by total assets*

EXHIBIT 7
Results of the Regression Models

Panel A: $\text{Default} = \alpha + \beta_1\left(RC \times \frac{EBIT}{TA}\right) + \beta_2\left(RC \times \frac{NI}{TA}\right) + \beta_3\left(RC \times \frac{CF}{TA}\right) + \varepsilon$

Simulation Classifier	Variable	Coefficient	R^2	Adj. R^2	F-Value	Variance Inflation
First Simulation: Expansionary/ Contractionary Cycles by the NBER	Intercept	0.192				
	$RC \times \frac{EBIT}{TA}$	-0.691***	0.071	0.069	37.21***	1.162
	$RC \times \frac{NI}{TA}$	-1.688***				1.338
	$RC \times \frac{CF}{TA}$	-0.024				1.168
Second Simulation: Positive/ Negative Percentage Changes in the CCI	Intercept	0.194				
	$RC \times \frac{EBIT}{TA}$	-1.258***	0.108	0.106	54.61***	1.214
	$RC \times \frac{NI}{TA}$	-1.493***				1.384
	$RC \times \frac{CF}{TA}$	-0.002				1.170

Panel B: $\text{Default} = \delta + \gamma_1\left(BC \times \frac{EBIT}{TA}\right) + \gamma_2\left(BC \times \frac{NI}{TA}\right) + \gamma_3\left(BC \times \frac{CF}{TA}\right) + \omega$

Simulation Classifier	Variable	Coefficient	R^2	Adj. R^2	F-Value	Variance Inflation
First Simulation: Expansionary/ Contractionary Cycles by the NBER	Intercept	0.184				
	$BC \times \frac{EBIT}{TA}$	-1.485***	0.069	0.067	36.24***	1.224
	$BC \times \frac{NI}{TA}$	-2.070***				1.407
	$BC \times \frac{CF}{TA}$	-0.163				1.175
Second Simulation: Positive/ Negative Percentage Changes in the CCI	Intercept	0.163				
	$BC \times \frac{EBIT}{TA}$	-2.673***	0.108	0.107	54.94***	1.338
	$BC \times \frac{NI}{TA}$	-0.722*				1.627
	$BC \times \frac{CF}{TA}$	0.003				1.273

Panel C: $\text{Default} = \lambda + \eta_1\left(RC \times BC \times \frac{EBIT}{TA}\right) + \eta_2\left(RC \times BC \times \frac{NI}{TA}\right) + \eta_3\left(RC \times BC \times \frac{CF}{TA}\right) + \varphi$

Simulation Classifier	Variable	Coefficient	R^2	Adj. R^2	F-Value	Variance Inflation
First Simulation: Expansionary/ Contractionary Cycles by the NBER	Intercept	0.172				
	$RC \times BC \times \frac{EBIT}{TA}$	-0.769***	0.067	0.065	35.09***	1.182
	$RC \times BC \times \frac{NI}{TA}$	-1.196***				1.406
	$RC \times BC \times \frac{CF}{TA}$	0.004				1.213
Second Simulation: Positive/ Negative Percentage Changes in the CCI	Intercept	0.152				
	$RC \times BC \times \frac{EBIT}{TA}$	-1.366***	0.107	0.105	54.13***	1.297
	$RC \times BC \times \frac{NI}{TA}$	-0.395*				1.660
	$RC \times BC \times \frac{CF}{TA}$	0.058				1.340

*The exhibit portrays the results of the ratios' relevancy analysis. Panel A depicts the findings regarding the interactions between credit rating classes and the three accounting ratios in Equation (4). Panel B describes the findings concerning the interactions between business cycles and the three accounting ratios in Equation (5). Panel C presents the findings for the interactions between credit-rating classes, business segments, and the three accounting ratios in Equation (6). Each panel contains two parts; the first part designates the simulation derived from the expansionary versus contractionary business cycles defined by the NBER, and the second part represents the simulation obtained from the sign of percentage changes in the CCI. Within each part, we present the tested variables, the corresponding coefficients and their statistical significance, the R-square, the adjusted R-square, the F-value signifying the significance of the regression model, and the variance inflation factor as an indication for multicollinearity. The symbols ***, **, and * indicate significance at the 0.01, 0.05, and 0.10 level or better, respectively.*

and business conditions shows no connection to default likelihoods.

Panel C defines a higher resolution of interaction terms between the three accounting ratios and the specific states of nature constructed simultaneously from rating classes and business cycles. This test is meant to further examine the relevancy of these three ratios—representing the Z-score, O-score, and CFBM-score—to default chances when they occur in exclusive states of nature. As before, in both simulations, we discover such dependency for the EBIT and net income ratios, but not for the cash flow ratio.

SUMMARY AND CONCLUSION

In this study, we conduct a comparative analysis of three popular methodologies—the Altman [1968] Z-score, the Ohlson [1980] O-score, and the CFBM-score offered by Aziz, Emanuel, and Lawson [1988]—in different scenarios. We differentiate between the various states of nature by identifying certain months as being in expansionary or contractionary stages according to the NBER definition, or by computing the percentage changes in the CCI and splitting the sample into low and high S&P credit ratings. We also deploy a canonical discriminant analysis and propose a unique score for the examined states. These alternative scores often challenge the traditional approaches.

By contrasting the related ROC curves, we detect dissimilarities in the predictive power of the different models. We find that the Z-score is the best of all models in most states of nature. We recognize that the CFBM-score performs below average in most cases, except for the positive business segment by the percentage changes in CCI. We discover that the O-score performs exceedingly badly in most states of nature, except for two cases: 1) the expansionary business cycle and high credit ratings, and 2) the positive percentage changes in CCI and high credit ratings.

We further demonstrate the economic importance of these differences in predictive power between the examined models by simulating realistic lending schemes.

Finally, and most importantly, we analyze the source of the variation in results. We find that profitability measurements distinctively affect default odds among different rating categories and within distinct business segments, but cash flow quantities do not.

ENDNOTES

[1]The only difference between the two indices is that the consumer sentiment index has two monthly releases, a preliminary and a final reading.

[2]For purposes of robustness, we also follow the O-score implementation by Griffin and Lemmon [2002]. Although some differences exist between these two measurements, the results are rather similar. Therefore, we present the findings based on the original Ohlson [1980] methodology, while omitting the insignificance coefficients of the two exchanges; the NYSE and the AMSE.

[3]Aziz, Emanuel, and Lawson [1989] find their CFBM-score more conservative than the Altman [1968] Z-score, yet both approaches share similar effectiveness in classifying bankrupt and non-bankrupt firms.

[4]The CDA and the MDA are essentially the same statistical methods. Throughout this study, we favor the use of the first term due to our recurring deployment of the CANDISC procedure in SAS.

[5]This test has been discussed and used in the finance literature by, among others, Kealhofer [2003]; Stein [2003], and Jarrow and Van Deventer [2004].

[6]When default occurs, assuming negligible distress and bankruptcy costs, Altman, Resti, and Sironi [2001] define RR as the ratio between the asset value and the face value of debt. To better demonstrate the robustness of our findings we allow different RRs in the simulations.

[7]These three ratios best represent the core essence of the traditional scores. The *operating income scaled by total assets* is the dominant factor affecting creditworthiness in the Z-score. The *net profit scaled by total assets* is the central component in the O-score. The *operating cash flow scaled by total assets* is the principal module behind the CFBM-score.

[8]To save space we do not present all the ROC curves in all states of nature, but we do demonstrate a few selected ones.

[9]This result somewhat contests previous studies. Marchesini, Perdue, and Bryan [2004], among others, find that traditional bankruptcy prediction models fail when compared to specific-state scores and when tested among high-yield bonds.

[10]When we execute single regression analysis with all the interaction terms from Equations (4), (5), and (6) combined together, not surprisingly we find strong multicollinearity. However, when separating these regression models, none of the variance inflation factors exceed 10, and therefore the standard errors are not inflated.

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