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By Warren Miller and James P. Harrington

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In light of the current economic turmoil and continuing uncertainty in credit markets, it's even more important that business appraisers accurately identify distressed companies and their potential for default. Developing cost of capital (discount) rates in this economic environment presents an additional challenge. Recently, Morningstar's valuation research team reexamined two bankruptcy prediction models—the Z Score and Distance to Default models—and assessed their predictive power. We also studied a simple, single-variable model based on the ratio of total liabilities to total assets (TLTA), since even individual accounting ratios and measures of capital structure may predict bankruptcy potential to some degree.

As a result, we've developed a new "Distance to Default" (D2D) model, which we believe better assesses a company's health and leads to more accurate public and private company valuations.

The models and their current application

The Z-Score, developed by Professor Edward Altman, is perhaps the most familiar model for predicting financial distress (Bemmann 2005). Altman identified five common accounting ratios that significantly predict default. Each factor is intuitively appealing to the business appraiser (as well as investors and lenders) because it captures a different credit-relevant aspect of a company's operations.

Financial innovation paved the way for further development of corporate default prediction

models, including the option pricing model by Black and Scholes in 1973, and refined by Merton in 1974. During the late 1980s, KMV (now Moody's KMV) developed the first commercialized structural default prediction model. Morningstar's D2D model further modifies these earlier works.

The D2D model is less intuitive than the Z-Score because it does not specifically address the cash accounting values that practitioners and professionals typically examine in a default or bankruptcy scenario. The D2D model considers a company's equity as a call option on the firm's assets with a strike price equal to the book value of its liabilities and a market price equal to the market value of the firm's assets. D2D describes the probability that this hypothetical call option will end up worthless—in effect, the potential that it expires with the firm's assets (the option's underlying asset) below the strike price (the book value of the firm's liabilities).

Commercial applications. The Z-Score is currently being used commercially; for instance, Z-Score is used to rank high financial risk companies in the Duff & Phelps "High Financial Risk Portfolio Supplement" (published August 2009). Traditionally, Morningstar has not cleansed our size premia (in *Stocks, Bonds, Bills, and Inflation*, formerly Ibbotson's), preferring to commingle healthy and distressed companies.

Now that we have a more reliable method of identifying distress, we have reopened this "cold case." For example, we currently use the D2D model to calculate a daily "Financial Health Grade" for all public companies in our Morningstar.com equities database. In addition, we may use D2D to develop a Default Premium for commercial application in private company valuations, which appraisers could use to adjust the cost of equity for firms they deem to be at measurable risk of default. We could also scrub distressed

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firms from our size premium data using D2D instead of Z-Score.

Our comparison of the Z-Score and D2D models is not a contest; rather it sheds light on the strengths and weaknesses of each while giving appraisers a better understanding of the current tools to evaluate the creditworthiness of public and private companies.

Test setup: collecting and refining the data

We first compiled a Master Bankruptcy List of 502 companies that defaulted between March 1998 and June 2009 (from Bloomberg data). Next, we extracted the necessary data from Distance to Default values provided by the Center for Research in Security Prices (CRSP) (Univ. of Chicago Booth School of Business). We then calculated Z-Score and TLTA values with data from Morningstar's Equity XML Output Interface, and transformed each rating into a percentile score using uniform breakpoints based on all the data over a 10-year history. The higher the percentile, the more "dangerous" (prone to default) a company was rated. Finally, we matched our Master Bankruptcy List with the three percentile datasets (Distance to Default, Z-Score, and TLTA). Although these overlapped, they did not include identical company-date records.

What we tested. The best way to compare the performance of credit-scoring models with non-identical sample sets is to measure their ability to differentiate between the companies that are most likely to go bankrupt from those that are least likely to go bankrupt (Bemmann 2005). Specifically, we tested each model's ability to rank companies from least to most likely to declare bankruptcy, as well as the rankings' durability and stability. We also performed two tests of each model's cardinal ability to predict bankruptcy.

Results: Ordinal

Figure 1 plots the cumulative percentage of bankruptcies on the y-axis and the ratings percentiles on the x-axis for each of the three models (plus a non-predictive model and an ideal model). This graph is called a Lorenz curve (after economist

Max Lorenz), and is also known as a cumulative accuracy profile (CAP). It typically measures the inequality of a distribution.

Each point on any of the lines in Figure 1 can be interpreted as “the percentage of actual bankruptcies that occurred in the bottom x rating percentile over any 1-year time horizon.” For example, at Point A on the dashed 45-degree line, 50% of the companies that went bankrupt originally received a credit rating that placed them in first 50 ratings percentiles (relatively safe); and 50% of the companies that went bankrupt originally received a credit rating that placed them in last 50 ratings percentiles (relatively unsafe). A quick inspection reveals that at *all* points on the dashed 45-degree line bankruptcies are distributed equally among ratings percentiles. Unfortunately, a ratings model that indicates a “safe” rated company is just as likely to go bankrupt as an “unsafe” company has no real predictive ability.

Less Safe

What would an ideal credit-scoring model look like? The straightforward answer follows from our analysis of the non-predictive model: the ideal credit-scoring model would *maximize* the inequality of bankruptcy distribution. Point B in Figure 1 is an example of an unequal distribution. At Point B, 18% of the companies that eventually went bankrupt had received a credit rating from the TLTA model that placed them in first 50 ratings percentiles (relatively safe) within one year prior to bankruptcy, and 82% of the companies that eventually went bankrupt had received a credit rating that placed them in last 50 ratings percentiles (relatively unsafe) within one year of bankruptcy. Thus the TLTA model provides better differentiation among and prediction of bankruptcy-prone companies than the hypothetical model represented by the dashed 45-degree line. The more a model’s line bows out towards the lower right, the greater the inequality of bankruptcy distribution and the more predictive the model. In Figure 1, the “Ideal” credit scoring model does not bow out all the way into the corner, since one company could not represent 100% of the bankruptcies.

Our primary indicator for measuring inequality is the Accuracy Ratio, which is the ratio of the area between the non-predictive (random 45-degree) line and the scoring system’s curve, and the non-predictive line and the ideal scoring system’s curve. (The Sidebar on page ??? explains the Accuracy Ratio in greater detail.) Accuracy Ratios range from 0 (no predictive ability) to 1 (ideal predictive ability). Table 1 summarizes the Accuracy Ratios of the credit-scoring models shown in Figure 1.

	Accuracy Ratio
Ideal Predictive Ability	1.00
Distance to Default	0.70
TL/TA	0.60
Z-Score	0.60
No Predictive ability	0.00

Table 1: Accuracy Ratios

In our study, we found that Distance to Default has the greatest accuracy ratio of all the models and therefore has superior ordinal performance to the Z-Score or the simple TLTA model. In addition, D2D approaches the ordinal rating accuracy of credit rating agencies Moody’s and S&P, which have estimated accuracy ratios for large public companies of 68% to 85% and 60% to 83%, respectively (Bemmann 2005).

The cumulative accuracy profile in Figure 1 provides more detail than the Accuracy Ratio alone. Specifically, we can see that the Z-Score holds its own against Distance to Default and is superior to the TLTA model for companies at a low risk of bankruptcy. As the risk of bankruptcy increases, however, the Z-Score’s ordinal ranking ability deteriorates, as demonstrated by its concavity between the 80th and 100th ratings percentiles.

Durability results

The ordinal ranking ability of any bankruptcy prediction model would presumably decay as the allowable time-horizon for bankruptcy lengthens. Figure 2 shows the ordinal predictive capability of all three models over one- to 10-year bankruptcy time-horizons.

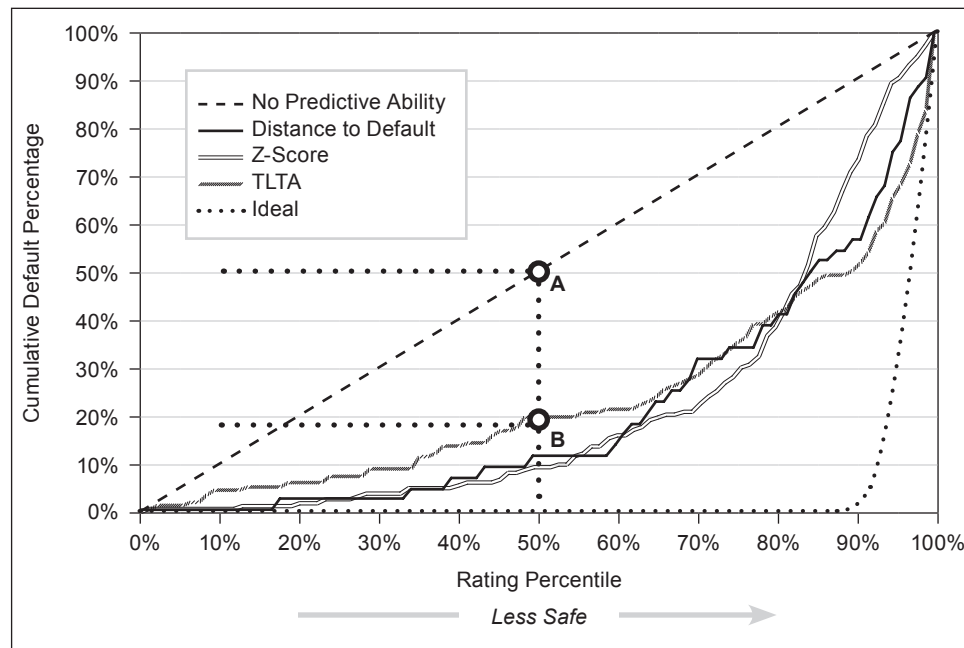


Figure 1: Cumulative Accuracy Profiles (1-year horizon)

Figure 2 demonstrates that Distance to Default's predictive ability is superior to the other two models over all bankruptcy time-horizons (higher is better). The widening spread between D2D and the other two models also demonstrates that the decay of its predictive ability is less than that of the other two, meaning D2D produces a more durable signal.

Stability results

Rating stability can determine the potential applications of a credit scoring system. In most models, ordinal and cardinal accuracy are at odds with rating stability; i.e., accuracy must be sacrificed for stability and vice versa. Drift distance is a measure of how each model's ratings vary from period to period, from 0 (maximum stability) to 9 (minimal stability).

Figure 3 shows that Distance to Default is the least stable rating system, followed by the Z-Score, and then the TLTA. This is expected, since market-based model inputs are typically more volatile than accounting-based inputs and D2D relies more on the former but TLTA and Z-score rely primarily on the latter.

Cardinal results

Our secondary performance tests gauged each model's cardinal ability to predict bankruptcy. Table 2 examines the default rates of the companies to which the models assigned the lowest risk.

Of the three models, Distance to Default proved to be most predictive of bankruptcy in absolute terms. On average, the most recent D2D percentile before a bankruptcy event was 91. In addition, the D2D had the lowest occurrence of bankruptcies in its best-rated quintile of companies. The Z-Score placed second in both measures, followed by TLTA.

Summarizing the study

Distance to Default outperformed the Z-Score and our univariate TLTA model in both ordinal and cardinal bankruptcy prediction. Curiously, the Z-Score's predictive ability is nearly equal to the other two models when ranking relatively safe companies, but performs worse in situations when the bankruptcy probability is high. Compared to the other two models, Distance to Default also had a higher average rating just prior to bankruptcy and a lower bankruptcy rate for companies it had categorized as "safe."

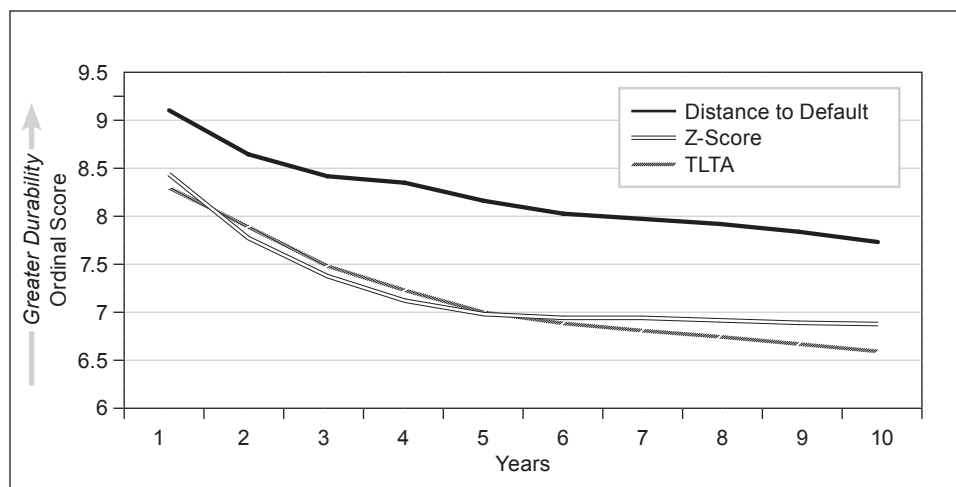


Figure 2: Ordinal Score over All Bankruptcy Time Horizons, 1 to 10 Years

If a bankruptcy signal is not durable and decays too rapidly to act on, then a predictive model will prove useless in practice. We found that all three models produced actionable scores. However, D2D generated more durable ratings, as its ordinal ability decayed at a slower rate than either of the other two models. It also displayed more volatile ratings than both the Z-Score and the TLTA model. This is intuitive, because D2D relies more on the volatile market-based inputs than accounting-based inputs.

One final note to appraisers: When valuing a business as a going concern, a firm is assumed to continue operations into the indefinite future. Does this mean that you need to remove distressed companies from public company risk premiums when applying the latter to the valuation of healthy, going

concern private entities? It does not. Although the firm is presumed to be a going concern, predictive ability is never 100%. Applying risk premium data based on a portfolio of primarily healthy companies with a small slice of potentially distressed companies acknowledges the less-than-100% chance that a subject firm will be perfectly healthy for the indefinite future.

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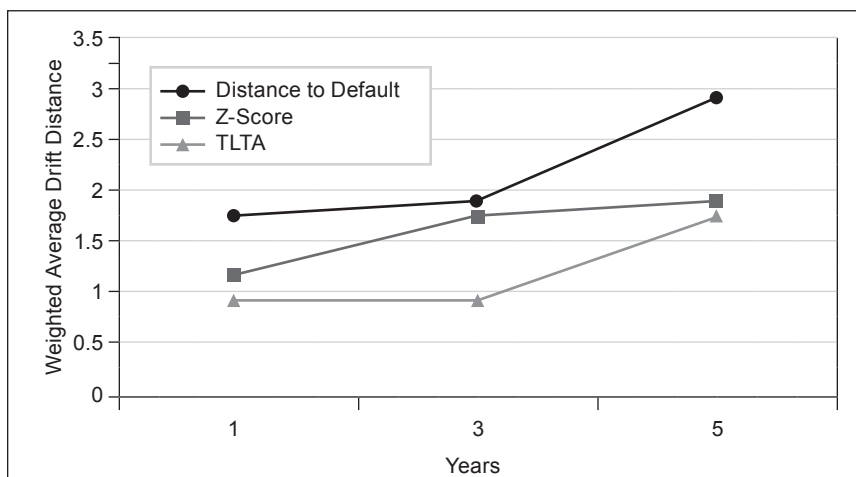
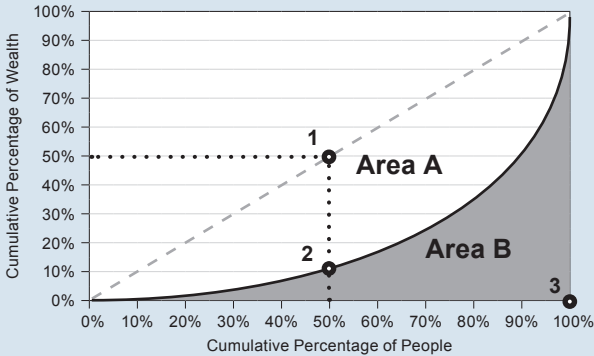


Figure 3: Weighted Average Drift Distance Over 1-, 3-, and 5-Year Horizons

Accuracy Ratio explained

Over one hundred years ago, U.S. economist Max Lorenz first used cumulative accuracy profiles to analyze inequalities in wealth distribution. For example, the dashed 45-degree gray line in the Figure below represents equal wealth distribution, since everyone has the same amount of wealth (i.e., at Point 1, the bottom 50% of people own 50% of the wealth).



In contrast, the solid line represents unequal wealth distribution: At Point 2, the top 50% owns 95% of the wealth. The more the solid blue line bows out toward the lower right corner, the greater the inequality of wealth distribution and an ever-smaller number of people own the wealth. If so, it follows that inequality increases as the ratio of the lighter area (A) to the larger light plus darker area (A+B) increases, ending at Point 3:

Measure of Inequality = Accuracy Ratio = $A / (A+B)$

This Accuracy Ratio is commonly called a Gini coefficient (after Italian statistician Corrado Gini).

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About the authors: **Warren Miller** is a Senior Quantitative Equity Analyst at Morningstar. Mr. Miller has passed all three CFA exams and authored the original whitepaper, "Comparing Models of Corporate Bankruptcy Prediction: Distance to Default vs. Z-Score," on which this article is based. The whitepaper is a free download at global.Morningstar.com/DistancetoDefaultResearch.

James P. Harrington, Director of Business Valuation Research in Morningstar's Financial Communications Business, reviewed and condensed the whitepaper for the *BVUpdate*. Mr. Harrington is the senior editor of the widely referenced *SBBI Classic and Valuation Yearbooks*, *Cost of Capital Yearbook*, and *Beta Book* (all formerly Ibbotson), as well as international and domestic cost of capital reports. He currently leads Morningstar's expanding investment in valuation research.

	Average Rating Before Default	Default Rate of Top Quintile
Distance to Default	91	0.5%
Z-Score	83	0.6%
TLTA	82	0.8%

Table 2: Cardinal Accuracy Measures