The Credit and Financial Management Review

A Journal for Credit and Financial Administrators

Volume 16, Number 2 Second Quarter 2010

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Subscriptions are $80.00 per year.

Submissions of articles or advertising opportunities should be directed to:

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Can You Trust Your Credit Model?

By: Jack Zwingli &
Tom White

Abstract

As the level of bankruptcies continues to run near historical highs – up 25% vs. the prior year through the first quarter of 2010, according to the American Bankruptcy Institute – credit managers continue to expand the use of credit models to identify companies at greatest risk of bankruptcy and related financial distress. Their motivation is both to lower risk and to cost effectively manage the credit review and approval process.

Credit models have clear advantages – they are relatively inexpensive, objective and effective – tirelessly crunching through numbers and algorithms to determine the companies at the greatest statistical risk of failure. Yet an over-reliance on less effective models can leave the user open to denying credit to creditworthy companies – or creating "false positives" as they are known in the statistical world. While it can be argued that the financial and reputational risks of "false negatives" – categorizing a company as low risk and creditworthy only to have it go belly up – are much greater than false positives, it is important to utilize credit models in a way that minimizes the elimination or restriction of credit for solid companies.

A Flaw in the Models

One very significant flaw in credit models – or in traditional fundamental research, for that matter – is a blind reliance on the validity and accuracy of corporate financial data. Prior academic research has focused on using either financial ratios or market data to predict future corporate bankruptcies. Yet both approaches share the same fundamental weakness: an assumption that the financial statement data underlying those ratios and prices are complete and correct.

History suggests otherwise, often painfully. This critique of bankruptcy (or credit) research is not new. In 2004, Balcaen and Ooghe addressed this issue: "researchers implicitly assume that annual accounts give a fair and true view of the financial situation of companies. However, it is clear that many annual accounts are unreliable and do not give a fair and true view."[1]

[1] Balcaen, Sofie and Hubert Ooghe. "35 Years of Studies on Business Failure: An Overview of the Classic Statistical Methodologies and Their Related Problems," Vlerick Leuven Gent Working Paper Series 2004/15.

It is possible to improve the credit model and credit scoring process by incorporating a measure of corporate trustworthiness. This article will review different approaches to building bankruptcy/credit models, comparing an approach introduced last year by Audit Integrity with two more well established approaches, the Altman Z-Score and the Merton Distance to Default models. It will review which approaches work best, and what the best approach is to reduce costly false positives. For the purposes of this article, bankruptcy risk is being equated to credit risk, as bankruptcy models form the basis for many credit models.

Building a Better Credit Risk Model – combining multiple risk factors to capture different types of risk

Substantial academic literature, in addition to practical business use, has supported two primary methods of estimating bankruptcy risk – one based on accounting factors, the other on market factors. Since both approaches are predicated on the accuracy of financial statements, the assumption was made that a measure of corporate integrity would identify yet another type of risk associated with bankruptcy – the risk that the company was misrepresenting accounting information or artificially manipulating market data through fraud or high risk behavior.

A report issued in May, 2010, by COSO, an independent accounting industry association, points out the risks associated with fraudulent financial reporting, based on a highly detailed review of fraud over a recent 10-year period:

> "Long-term negative consequences of fraud were apparent. Companies engaged in fraud often experienced bankruptcy, delisting from a stock exchange, or material asset sales following discovery of fraud – at rates much higher than those experienced by no-fraud firms."

Forensic accounting techniques and several measures of corporate governance (executive compensation, insider trading, officer turnover, etc.) have been found to be predictive of fraudulent behavior. One measure of fraud risk, the Audit Integrity Accounting and Governance Risk (AGR®) rating, uses proprietary forensic accounting and governance metrics to identify companies at greatest risk, based on a study of SEC fraud actions.

The next sections will cover three different approaches to measure bankruptcy (and, by extension, credit) risk – the venerable Altman Z-Score, the Merton Distance to Default approach, and a fraud risk approach using AGR.

The Altman Z-Score – an accepted approach to measure bankruptcy risk using key accounting ratios

The Altman Z-Score was first introduced in a 1968 paper by Edward Altman[2], and later revisited in 2000[3]. The original 1968 paper described a model for predicting bankruptcy among manufacturing companies.

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[2] Altman, E. "Financial Ratios, DIscriminant Analysis and the Prediction of Corporate Bankruptcy," **Journal of Finance**, September 1968.

[3] Altman, E. "Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA®Models", July 2000.

While there is, with knowledge gained from practical application of the Z-Score, reason to question some aspects of the statistical approach taken, there is no denying that even 40 years after it was first published the Z-Score remains an effective predictor of bankruptcy.

The 2000 paper expanded upon the basic foundation, adding variations for non-manufacturing, private and foreign firms. In its original form for manufacturing companies the Z-Score is calculated from 5 ratios, capturing basic measures of company liquidity (does it have sufficient capital to run the business?), leverage (does it have too much debt?), and profitability (is it making money?):

- Working Capital / Total Assets
- Retained Earnings / Total Assets
- Earnings Before Interest and Taxes / Total Assets
- Market Capitalization / Book Value of Total Liabilities
- Sales / Total Assets

The Z-Score was initially calculated once a year using data from annual reports. Using the most recent financial statements prior to the bankruptcy filing, Altman found that 95% of his 33 in-sample firms had a Z-Score below 1.8. Going another year further back, 72% of bankrupt firms registered Z-Scores below 1.8.

There are two significant concerns about the Z-Score approach. First, even if it is calculated quarterly, it has a tendency to lag the knowledge in the market. Also, there is the issue of false positives. By setting the cutoff at 1.8, approximately 35% of the universe of companies is identified as being at risk, or a "positive" result. As noted in the analysis to follow, this high level of inclusion leads to many more false positives than other approaches, adding to the real and opportunity costs of using a Z-Score approach to setting credit approvals.

Merton Distance to Default – using market data to determine the likelihood of default and bankruptcy

The use of current market data has the primary advantage of reflecting all available information about a company in the probability of bankruptcy. Default probability models have become widely used in evaluating credit risk, or the likelihood of a company defaulting on its debt. More recently, these Distance to Default (DD) models have been applied to determining bankruptcy probability, with results that match or exceed accounting-based models.

The key factors in a market-based risk model are:

Market Value of Assets – since the market value of a firm's assets is not readily observable, the DD model uses equity market prices to estimate and capture changes in the market value of assets

Asset Value Volatility – derived from volatility in equity prices, and incorporating differences in the company size, industry and geography

Book Value of Liabilities – captured from company financial statements

A well accepted implementation of a Merton DD model is presented by Bharath and Shumway[4]. In this paper, the authors describe a "naïve" form of the Merton model. The Merton DD model treats the equity of a firm as a call option on the firm's underlying value. This option is assumed to have a strike price equal to the book value of the firm's debt. Although the actual calculation is more complicated, in essence the Merton model assesses the probability of bankruptcy by considering the ratio of a firm's market value vs. the face value of the firm's debt. The Merton DD model can be calculated frequently, as the market data changes. For the AI-B, the DD component is calculated on a monthly basis using month end market data and the most recently published financials. This approach minimizes volatility, which is the primary drawback to a DD model.

Building a Better Bankruptcy (Credit) Risk Model

Both the Altman Z-Score and the Merton DD models have proven to be effective in identifying bankruptcy and credit risk, and are used by many credit managers to screen out bad risks or set credit limits. No approach, however, either qualitative or quantitative, is without drawbacks. An often quoted comment from noted statistician George Box sums up quantitative approaches – "Essentially, all models are wrong, but some are useful."

The primary drawback of the Z-Score is that it is built upon somewhat outdated information, and will not reflect recent changes in a company's financial or business condition. For the DD approach, the opposite can be true – short-term stock market volatility can lead to big swings in DD results, often driven by market sentiment or overall stock market movement, rather than by a significant deterioration of a company's financials.

In an attempt to build a "useful" bankruptcy model, it is pragmatic and reasonable to use as a foundation the approaches taken by Altman with accounting-based models, and by Merton with market-based models. Both approaches have been utilized with success and have stood the test of time. But neither addresses the critical shortcoming of a blind reliance on financial data. By adding in a fraud-based component to incorporate that risk, a working hypothesis can be established that a model based on all three components would be more predictive. This combined approach will be labeled AI-B throughout the rest of this article.

Comparing the three different models requires some changes to ensure that results are equivalent. The first challenge is simply standardizing the frequency of the various bankruptcy predictions. The Altman Z-Score as originally described was based on annual data from 10-K's and (for manufacturing firms) the market capitalization of the company. However, given the relatively small role market cap plays in the Z-Score (and its complete absence from the score for non-manufacturing firms,) the Z-Score as traditionally calculated would be unlikely to change substantially more than once a year. The Merton DD also uses some financial statement data, but it is largely driven by market capitalization and price volatility. As such, it can vary significantly even on a day to day basis. The AGR is calculated on a quarterly basis using Trailing-Twelve-Month (TTM, a method that smoothes short-term volatility) financial data. Since it has no market-based component the AGR changes just four times a year.

[4] Bharath, Sreedhar T. and Tyler Shumway, "Forecasting Default with the Merton Distance to Default Model," May 2008.

In creating the AI-B , these various reporting frequencies were reconciled by creating a monthly score, based on the latest available data from various data sources. For example, a typical AI-B rating for February 2010 would be comprised of market data as of January 31, 2010 along with the most recent financial statement data available, which for most firms would be for the quarter ending September 30, 2009.

For the purposes of this comparison between the three approaches, monthly data is used. This required little or no modifications for the AI-B and Merton DD models. However, the Altman Z-Score required more substantial modification. Rather than using only 10-K data (which would force the Z-Score to use older financial statement data than was being used in the AI-B,) quarterly TTM data was used. This ensures that the fundamental data used by the Altman Z-Score, the Merton DD, and AI-B is sourced from the same financial statements. Likewise, all market data used is end of month data. The result is a monthly dataset of bankruptcy model predictions based off the same source data. This is the foundation for a sound comparative analysis.

The second component of the analysis is a dataset of actual corporate bankruptcies. To make the analysis meaningful, a clean, comparable dataset of bankruptcies was needed. For this, the out-of-sample dataset used in developing the AI-B was chosen (the dataset use to test the model, vs. the in-sample dataset used to build the model.) This dataset consists of 516 Chapter 7 and 11 bankruptcies filed between January 2005 and April 2010. Each of the three models has different data requirements. For example, the Merton DD and AI-B models require market capitalization data. This eliminates some of the sample of 516 bankrupt firms from the comparison, as some were not publicly traded, but had only issued public debt.

In order to calculate the Merton and AI-B models, it was required that the stocks be actively traded and liquid, thus ensuring meaningful pricing data. Additionally, the AI-B model is not run on the smallest 15% of firms by asset size. Finally, the Altman Z-Score and AI-B models don't address bankruptcy among utilities or financial firms. In the end, the sample of bankruptcies was limited to companies that had ratings for all three models. This substantially reduced the dataset to between 150 and 200 companies depending on the time horizon being studied, but ensured the analysis was done on a uniform set of bankruptcies.

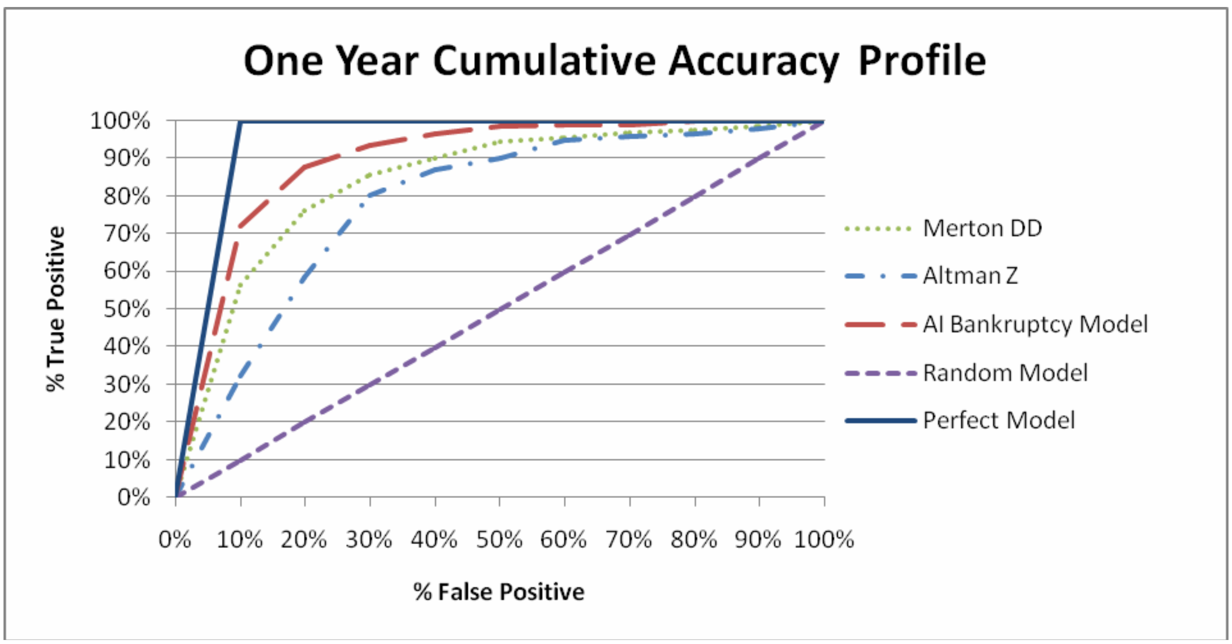
Which Model Performs Best?

The standard validation test for measuring the predictivity of a model – how well did the model predict the outcome it was built to predict? – is the accuracy ratio. Bringing this back to the concept of "false positives" discussed earlier, accuracy ratios measure the relationship between false positives (companies predicted to go bankrupt that do not) and true positives (companies that are correctly predicted to go bankrupt.)

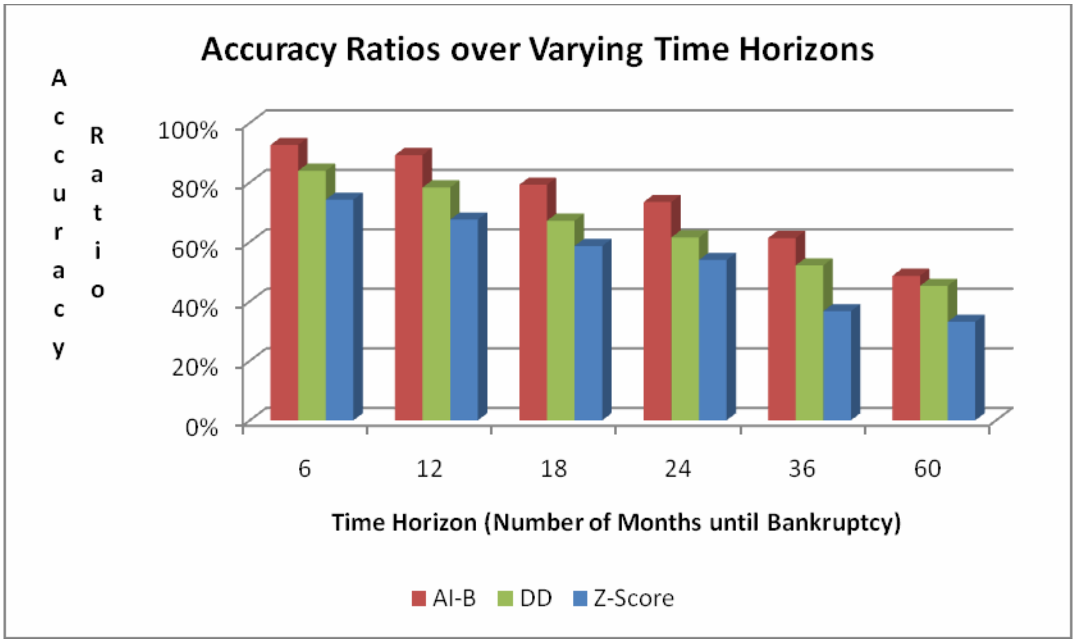
Accuracy ratios can be represented in a Cumulative Accuracy Profile, as shown in the graph on the following page. The Cumulative Accuracy Profile (CAP Curve) is a graphical representation of the tradeoff between true positives and false positives. The Cap Curves are bounded on top by a theoretically perfect model that would capture 100% of the bankruptcies in the worst decile of scores; the bottom boundary is a line with a 45 degree angle representing a random model where each decile would experience its proportional 10% of the bankruptcies purely by chance. The three models being compared all fall between these two extremes and their Accuracy Ratios measure how much of the area between these boundaries is covered by each model. Visually, the model that traces a curve most closely approaching the perfect model is the best.

The AI-B model traces the highest curve, reaching its peak of true-positives-to- false-positives sooner than either of the other two models and achieving an overall accuracy ratio of 89%. Merton's Distance to Default in second with an accuracy ratio of 78%, followed by Altman's Z-Score at 68%.

The next chart compares the three models in terms of how predictive each is at different time horizons. Overall, the results show that for each time horizon studied (6, 12, 18, 24, 36 and 60 months prior to bankruptcy) the AI-B outperformed both the Altman Z-Score and the Merton DD. The AI-B model performs particularly well relative to the other models 1 to 2 years in advance of bankruptcy. This suggests that incorporating the fraud risk indicator in the AGR score provides an effective leading indicator of financial distress. More to the point, it suggests that perhaps the first reaction of firms to duress may be an attempt to mask their underlying problems through aggressive accounting practices.

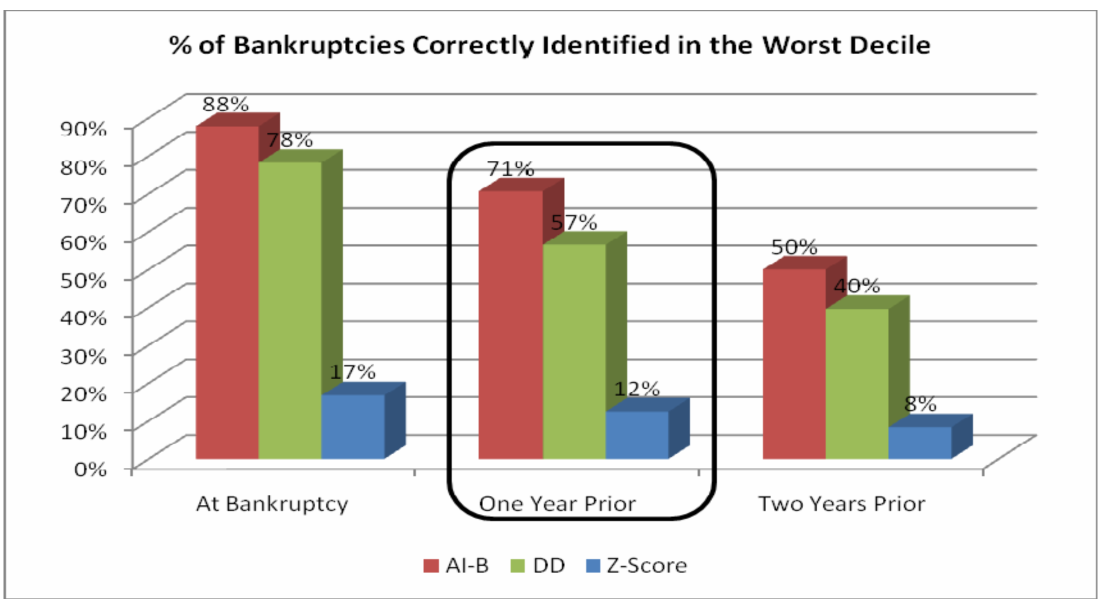


Any risk model must be predictive, providing ample advanced warning of the negative event. A one-year time horizon is most common, although many credit professionals take an even longer risk perspective.



Another, more "real world," way to measure the effectiveness of the models is to look at how many bankrupt companies were correctly identified as being in the "riskiest" category. Defining "riskiest" is somewhat subjective, and involves a trade-off between false positives and true positives, as discussed below.

As noted in the following chart, the AI-B approach is the best approach when looking at how many bankruptcies are captured in the bottom rated 10% of companies. At the time of bankruptcy, 88% of companies filing have an AI-B score in the bottom 10% of all companies rated, compared to 78% for DD and 17% for Z-Score. At a year prior to bankruptcy, a more relevant view, AI-B outperforms DD and Z-Score 71%/57%/12%.

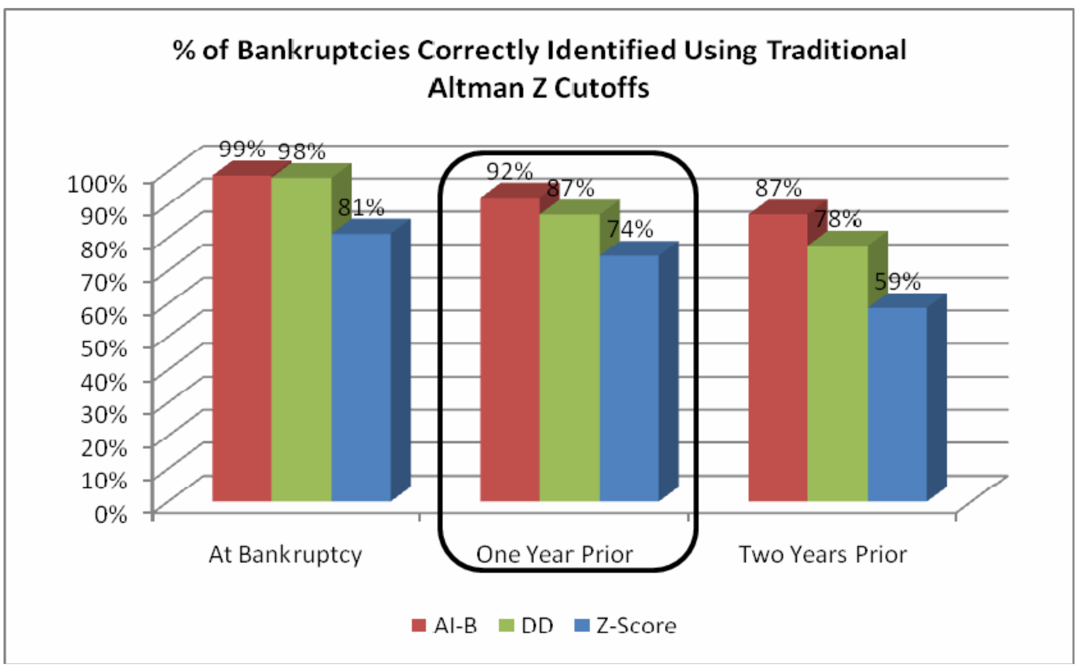


Limiting False Positives

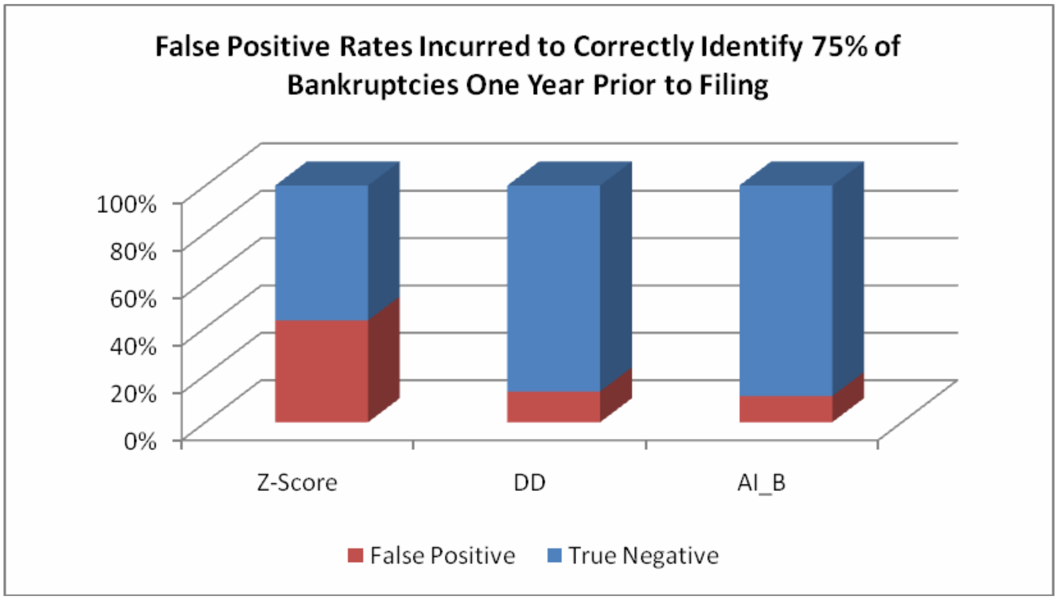
A bankruptcy or credit model with a high level of false positives has two costs associated with it. First, more time and resources are spent reviewing and researching companies incorrectly identified as being at high risk when, in reality, they are not. Second, potential business is turned away due to incorrect assumptions about the credit quality of companies flagged as risky.

As noted earlier, the traditional cutoff point for Z-Score has been at 1.8, or 1.1 for non-manufacturing firms. Using this cutoff captures approximately 75% of bankrupt companies – the true positives. But this cutoff also captures approximately 35% of the universe of companies rated. In other words, to capture 75% of bankruptcies using Altman Z-Score, you must eliminate 35% of companies from consideration. That means a lot of false positives – companies that are wrongly turned down for credit.

Adjusting the chart above to change the cutoff from the worst 10% to the Z-Score cutoff of 35% provides the results listed below. As noted, this cutoff captures 74% of bankruptcies using the Z-Score approach, vs. 92% correct for AI-B and 87% for DD. The AI-B approach worked better in every time horizon, with a very impressive 87% correct for the AI-B two years prior to bankruptcy vs. 59% Z-Score and 78% for DD.



Having looked at model usefulness in identifying true positives, what about the implications for false positives? Using the standard Altman Z-Score cutoff, and looking at Z-Scores a year prior to bankruptcy filing, it is found that ~35% of companies are mistakenly flagged as “risky” by the Z-Score. Using the equivalent cutoff for the AI-B, just 13% of companies are mistakenly flagged as “risky”.



By using the AI-B instead of the Altman Z-Score, an additional 22% of the universe of companies is correctly identified as "safe", *without sacrificing any accuracy.*

The Bottom Line on Bankruptcy Model Accuracy

While the traditional Z-Score cutoff of 1.8 seems to work quite well on the surface (~75% of companies that go bankrupt fell below that threshold a year prior to declaring bankruptcy), a closer look reveals substantial costs to a Z-Score approach. These costs can be measured in two ways. The first is through the elevated false positive rate associated with a Z-Score approach. Quite simply, using the Z-Score would cause a credit manager to needlessly dismiss over 20% of potential customers as bankruptcy risks to be avoided, at a sizable cost of lost business. Using the more accurate AI-B approach allows the credit manager access to this extra 20% of the population *without assuming any additional bankruptcy risk.*

Alternatively, using the AI-B allows the credit manager to dramatically reduce exposure to bankruptcy risk, *without any increase in false positives.* Using traditional cutoffs and a one-year time horizon, the AI-B allows credit managers to eliminate 92% of bankruptcy risk over a two year period, versus 74% for the Z-Score.

When compared to both the Z-Score and DD, AI-B has another critical advantage – by incorporating a measure of fraud risk, it improves the early warning capability of the model. In looking at the riskiest companies, as defined by the bottom decile, the AI-B accurately predicts71% of bankruptcies, compared to 57% for DD and 12% for Z-Score. The number predicted correctly two years out is 50%, 40% and 8%, respectively. That is a very sizable difference when making credit decisions.

Conclusion

Bankruptcy and credit risk models can provide a useful addition to the tools a credit manager has to lower risks while supporting business growth. It is up to the company and the credit manager to set acceptable thresholds for credit risk, balancing the need to avoid eliminating creditworthy clients (false Positives) with the need to identify future blow ups (true positives.) In the tradeoff between less risk and less revenues, credit scoring models can provide an objective, effective approach to optimizing that balance.

While the Altman Z-Score, and related accounting-based approaches, remains a useful predictor of future bankruptcies, superior risk models have emerged. Market-based approaches such as the Merton Distance to Default have been documented to provide superior results.

The comprehensive Audit Integrity Bankruptcy Risk Model, the AI-B reviewed above, combines accounting-based and market-based approaches with a unique third perspective on risk – the reliability of the financial data used to run many models, or, more simply, fraud risk. Incorporating this fraud-based component presents the highest accuracy and the greatest financial benefits.

Jack Zwingli is the CEO and Tom White is the Director of Quantitative Research for Audit Integrity. Audit Integrity is the leading provider of accounting and governance risk analysis on public companies. Through the forensic study of the factors behind fraud, Audit Integrity's proprietary quantitative modeling effectively detects and measures fraud and transparency-related risks in over 12,000 publicly traded corporations in North America and Europe. The proprietary Accounting & Governance Risk (AGR®) rating is a measure of corporate integrity based on forensic accounting and corporate governance metrics, and is an indicator of aggressive corporate behavior which can put stakeholders at risk.

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