Read the Crowdsourcing Enhancement white paper (7/26/16), a supplement to this document, which explains how the FRISK® score has now achieved 96% accuracy.

The CreditRiskMonitor FRISK® Score

EXECUTIVE SUMMARY

This white paper explains the purpose of the FRISK® score, its general design, and describes a July 2014 revision of the score model. As a result of this update, the score is now shown to be able to capture 95% of bankruptcies occurring during the subsequent 12 months in its "high-risk" categories (1-5). The FRISK® score proves to be significantly more accurate than the Altman Z"-Score when the two are compared. This is a significant improvement in performance for Credit and Procurement applications.

Introduction

CreditRiskMonitor has developed a suite of analytical tools to help credit and procurement managers identify and keep track of problem companies in their portfolio. The CreditRiskMonitor FRISK® score is a central component of this suite, proving effective at helping users in identifying high-risk businesses showing financial stress and providing early warning for managers to take action. The FRISK® score was launched in 2007 and provided early warning to users prior to the economic downturn that became the Great Recession. The graph in Figure 1 shows the population fraction of "high-risk" companies prior to, during and after the Great Recession (yellow area): roughly doubling from June 2007 to June 2009. The percentage of high-risk companies increased prior to the start of the recession. The FRISK® score was clearly sensitive to increasing financial risks.

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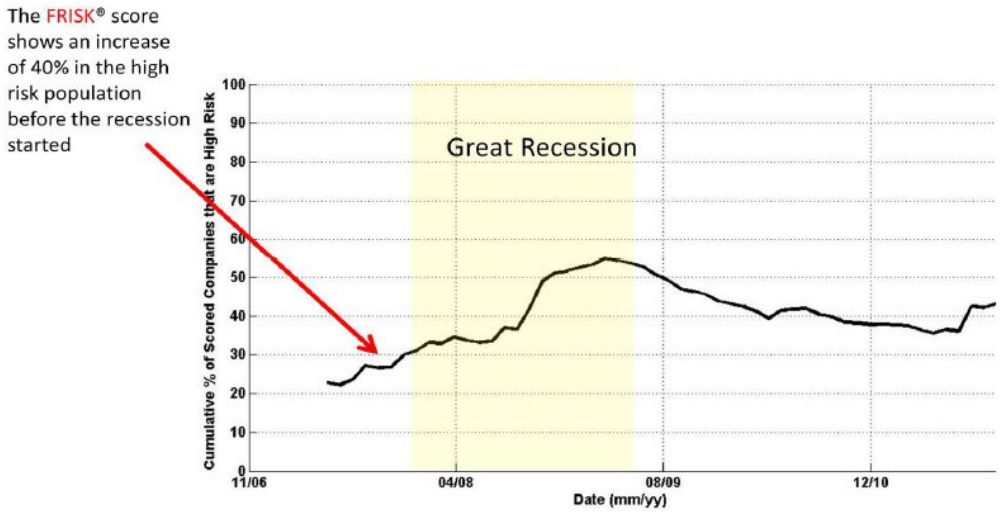

Figure 1. The FRISK® score indicated a doubling of risky companies during the Great Recession.

CreditRiskMonitor periodically undertakes recalibration of the FRISK® score to account for changing credit conditions in the market. The Company also uses this opportunity to introduce improvements in model performance. This document discusses the 2014 revision of the score.

The nature of automated credit scoring

In the past 20 years the use of automated credit risk models has expanded significantly because they provide a convenient and accurate summary of a company's financial condition and its ability to meet its payment or delivery obligations. Managers having to track hundreds or even thousands of companies can use credit scores to focus their attention on those companies that are weakest in their portfolio. This focus enables them to make better use of limited resources while at the same time improving bottom line performance.

Credit scoring was popularized in the consumer finance industry by banks that needed a more consistent, efficient way to approve and track the risk of millions of loans. This need drove the growth of the consumer credit bureaus and their credit scores. These scores take into account a large number of data items reported to the bureaus on each consumer, but it is the payment behavior on each of their commitments (e.g., credit cards, loans, bills, etc.) that is most important in providing a timely view of a particular consumer's credit risk.

Growth in the use of commercial credit scoring has developed more slowly, but followed a similar trajectory. Most commercial credit scores take into account a business' payment behavior on its trade accounts along with information such as liens, lawsuits, etc. Like consumer credit scores, most commercial credit scores are heavily impacted by the company's recent payment history. The intuitive "story" behind this is that as a company's financial condition degrades, trade credit becomes one of the few ways available to finance operations. By paying vendors more slowly, companies can reduce cash out-flow. Therefore, slow payment is a primary indicator used to identify companies in financial stress. Also, because the vast majority of companies are private and don't publish financial statements, payment information is one of the few types of objective, numerical data that is readily available on most companies. So, these types of credit models have proven effective and useful in evaluating private companies.

As noted above, the vast majority of companies are private. Most are very small, with no employees (only a sole proprietor works there). In the United States, there are (as of 2014) only about 6,000 publicly listed companies (corporate groups) in operation out of an estimated total of over 25,000,000 companies. But while they are small in number, these publicly listed firms are very large in size and most are global in their operations, with many subsidiaries. Together they represent nearly half of the accounts receivable and accounts payable of all companies. Larger businesses (public or private) will have significant exposure to public companies either as customers or vendors, or both. It is the typical experience of CreditRiskMonitor subscribers that while the vast majority of customers and vendors are smaller private companies, 40-50% of the dollars at risk are with publicly traded companies. So, managing financial risk requires a definitive approach to evaluating public companies.

It is commonly assumed that using models largely driven by payment behavior are appropriate in evaluating all companies, including those that are publicly listed. However, we have conducted research on this question, and find an important difference in the behavior of public companies versus private companies. Our study has shown that the link between payment behavior and financial condition for public companies is weak.[1] Large public businesses in good financial health can have relatively poor payment histories, because they elect to pay late. On the other hand, public companies in financial stress can maintain access to other sources of credit, and more often than not they maintain timely payments to vendors up until the day they file for bankruptcy. So, financial risk models designed for private companies – weighting payments data heavily in their calculation – tend to be far less useful in evaluating publicly listed companies.

Fortunately, both financial regulation and the need to satisfy investors results in a significant amount of information being available on publicly traded companies that is useful in understanding their current and future financial condition. The CreditRiskMonitor FRISK® score incorporates much of this information to produce a superior score.

[1] https://www.credittoday.net/public/How-to-be-less-surprised-by-a-large-customers-bankruptcy-or-Demystifying-the-cloaking-effect.cfm

Types of scoring models

There are several types of scoring models designed for evaluating public companies[2]: those based on financial statements, those based on stock market information (e.g., Merton type models such as the Moody's KMV score[3]) and agency bond-issuer ratings. A number of models combine multiple sources of information (e.g., the FRISK® score) to produce an overall credit score that improves on the shortcomings of any one approach.

Financial risk assessment based mainly on financial statement information has been in use for more than 100 years. Modern automated statistical credit models have a more recent vintage, with one of the earliest models, the Altman Z"-Score[4], first produced in the late 1960's.

The ratings produced by the bond rating agencies (technically known as Nationally Recognized Statistical Rating Organizations or "NRSROs" designated by the U.S. Securities and Exchange Commission) are generally not mechanical scores, although statistical models are often part of the analytical process. Agency ratings are generally produced by committees of experts in various industry groups, with each organization producing a rating, which is an ordinal ranking of their opinion of a company's or particular debt instruments (which can include credit enhancement vehicles) credit risk. These agencies have produced ratings on many types of financial instruments, but from a commercial credit manager's perspective or a procurement professional's perspective the ones of interest are called "issuer ratings," principally an assessment of the company's ability to pay its senior unsecured debt. Despite recent controversy surrounding the NRSROs ratings of mortgage-asset-backed and related securities, their corporate issuer ratings have proved generally effective in identifying companies showing high financial stress.

While agency ratings are effective in anticipating financial stress, the total number of companies rated is relatively small. Admittedly, these tend to be the largest companies, representing the largest exposures in a company's portfolio, but it is a small fraction of the roughly 40,000 traded companies that file financial statements with the public authorities worldwide. Also, because of the detailed methods by which ratings are produced by the rating agencies, including mandatory reviews by committees, these ratings tend to lag current conditions. In a rapidly changing business environment, they may not reflect the current situation for a particular company.

Mechanical scoring models using financial information have the advantage that they can offer broader coverage of more companies than are rated by the bond rating agencies.

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[2] And for private companies if financial statement data is available

[3] "Moody's KMV" is a trademark of Moody's Investors Service

[4] Altman, E.I. (1968) "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy" *Journal of Finance* 23: 189 - 209

The Altman Z"-score is one such broadly used model. As previously mentioned, the original version of the Z"-score was developed by Dr. Edward Altman in the late 1960s. He has also developed a number of versions since. The Z"-Score was developed in the late 1970's and is available on the CreditRiskMonitor website. The model uses four distinct financial ratios, which are combined to produce a continuous score suitable for evaluating the financial stress of industrial and service sector companies. As this score depends on financial statement information, it can only be updated when new annual or interim financial statements are produced by a company commonly just once every 90 days. The Z"-score model is also heavily influenced by balance sheet information, so the picture provided by the other financial statement tables (e.g., income and cash flow) is not as heavily weighted.

In the 1970's Professor Robert Merton wrote a seminal academic paper in the field of finance[5]. In that paper, he showed that stock market data can provide information as to the financial risk of a company. This is consistent with the efficient market hypothesis, which says that all benefits and risks about a stock are reflected in its stock price and its volatility. While this hypothesis is not strictly true, and some of the related drawbacks of this approach are discussed below, in the past 30 years the Merton model method (and its variations) has proved to be a useful tool in predicting default and bankruptcy. Like the Z"-Score, the Merton model is supported by a large body of published academic research. There is a common-sense reason why there should be a relationship between a company's financial risk and its stock market performance. Stockholders have the lowest seniority in recovering their investment in the event a company is dissolved; therefore, they are very sensitive to the risk of insolvency for a company.

The significant benefit of the Merton approach is that it can provide financial risk information on a daily basis based on the change in share prices of companies due to their trading on stock exchanges. One of the drawbacks of the Merton approach is that stock performance is not only influenced by the market's view of a particular company, but also by the behavior of the market or industry as a whole. In addition, the stock market sometimes overreacts to news about particular companies. For both of these reasons, the Merton model's estimate of a company's financial risk will itself be more volatile than the other methods of estimating financial risk.

The CreditRiskMonitor FRISK® score

Each of the risk models discussed above has strengths and weaknesses. Financial statement based models may not reflect the current condition of the company, in a similar fashion ratings are only updated when one or more of the rating agencies reviews a company. Stock market based models suffer from the same effects of over-

[5] Merton, R.C. (1974) "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates" *Journal of Finance* 29:449-470.

reaction seen in the markets frequently. It is reasonable to expect that by combining a number of these credit risk proxies, a model which mitigates some of the shortcomings and reinforces their strengths can be built. The CreditRiskMonitor FRISK® score achieves this, improving on the performance of each while mitigating their individual shortcomings. In particular the score utilizes:

- Stock market data – By using market capitalization, dividend information and stock volatility the score can capture changes in the market's daily view of the financial risk of a particular company.
- Financial ratio data – The score uses a number of ratios, including the Altman Z"-Score ratios, as well as cash flow-related items to incorporate the financial statement view of risk.
- Ratings – Although forming a small universe, ratings have in general proven very predictive of financial risk.

The FRISK® score combines the available data elements above to produce better estimate of risk than any one component. Plus, because of the variations in data availability, the model is designed to calculate a score from whatever data is available, whenever possible. For example, many companies are not rated; so the internal functioning of the FRISK® score handles this "missing bond issuer rating" situation seamlessly.

Model development data and bankruptcy analysis

The CreditRiskMonitor database was used to develop the FRISK® score using company data and bankruptcies between 2003 and 2013. This period covers 9,600 unique businesses and includes 580 U.S. public company bankruptcies.

Many financial risk models use default as the event that defines financial distress. Using default makes sense for bond investors, because it is an event of consequence to bondholders, although the definition of "default" isn't always consistent. There are many forms of technical default which may not be indicative of true financial distress. Also, some defaults are poorly publicized. Plus, many public companies have no public debt on which to default. Bankruptcy is an alternative event defining extreme financial stress. All bankruptcy events are a clearly defined matter of public record. Bankruptcy (whether Chapter 7 or 11) is a severe event, much more indicative that the company has been in financial distress over a period prior to the filing. So, the FRISK® model uses bankruptcy as the event that defines financial distress rather than debt default.

The model optimization was performed using survival time analysis[6]. Each company's input data was determined at different starting times and the time gap between each

[6] R. London, "Survival Models – and their estimation", ACTEX 1997

start time and either bankruptcy or the end of the data window was measured. The survival time was then used to determine the influence of input data on bankruptcy risk.

Model output and performance

The output of the FRISK® model is an estimate of a business' probability of filing for bankruptcy in the subsequent twelve months based on the development dataset. This value is then converted to a FRISK® score which varies between "1" (worst) to "10" (best). Table 1 below shows the mapping between FRISK® scores and probability of bankruptcy:

FRISK®	Low *pB** (%)	High *pB*(%)
10	0.00	0.12
9	0.12	0.27
8	0.27	0.34
7	0.34	0.55
6	0.55	0.87
5	0.87	1.40
4	1.40	2.10
3	2.10	4.00
2	4.00	9.99
1	9.99	50.00

Table 1. FRISK® scores and the associated probability of bankruptcy ranges.

The FRISK® score map is divided into three regions to highlight the level of credit risk associated with each, scores between "1" to "5" are marked red and are associated with an above-average level of credit risk, "6" to "8" represents an intermediate level of risk (in blue), and "9" and "10" (in green) represents the lowest level of credit risk.

A number of metrics have been developed in the past to evaluate credit model performance. The technique used here to evaluate the final model performance is the "Receiver Operating Characteristics" (ROC) method which has a long history in statistical model development[7]. The method compares the true positive rate "TPR" (i.e., the fraction of companies positively identified as likely to go bankrupt, for a given risk threshold, that do go bankrupt) with the false positive rate "FPR" (i.e., the fraction of

[7] R.J Irwin and T.C. Irwin, "Appraising Credit Ratings: Does the CAP Fit Better than the ROC?", IMF Working Paper WP/12/122, May 2012

companies positively identified as likely to go bankrupt, for the same risk threshold, that do not file for bankruptcy). Every risk threshold has a set of two values (FPR, TPR) associated with it, and by changing the threshold values an ROC graph can be generated as shown in the figure below:

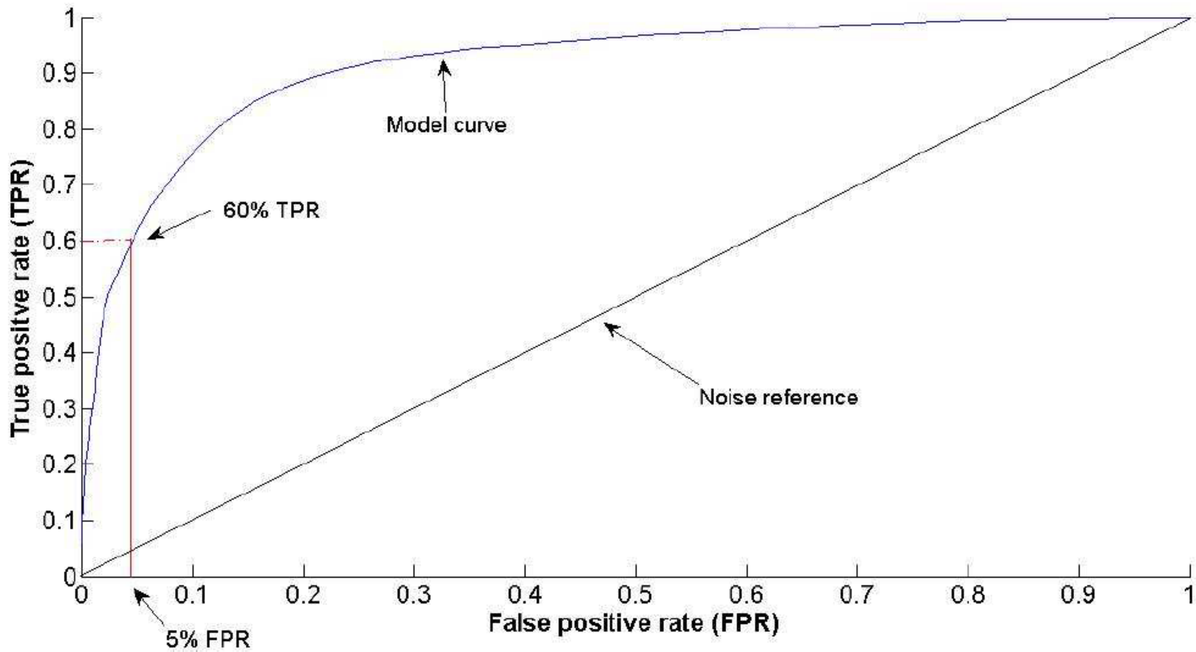

Figure 2. The ROC curve, a commonly used statistical evaluation method, shows the accuracy of the FRISK® score. 60% of bankruptcies are identified in just the "worst 5%" of all companies scored.

The blue curve in Figure 2 shows the FRISK® model ROC curve. The black line is a reference random curve: it shows how a model whose predictions were "random" might perform. The higher the model's ROC curve is above the reference curve the better the model. Better models will have a higher TPR for a given value of FPR. The ROC curve offers additional insight for Credit and Procurement applications, for which it is also important that the curve rises quickly at the left. In these applications, professionals seldom have the flexibility to reject a large fraction of companies. So the ability to identify a large fraction of financially stressed companies in the first 10% or 20% of the population is a valuable attribute of a financial risk model. The ROC curve makes it easier to see that the FRISK® score offers this benefit.

A related benefit of all financial risk models is their ability to focus the user's attention on a much smaller fraction of the corporate universe that is deemed high-risk. This focus enables professionals to be more efficient in their analytical work. Figure 2 shows that the FRISK® at a value of 5% FPR captures 60% of bankruptcies. What this means is that when the model is considering just 5% of the overall business universe as being high-risk, it nevertheless captures 60% of all bankruptcies in this small group.

The FRISK® is proven effective in identifying high-risk companies as shown in Figure 3. The figure shows model performance between the years 2007 and 2013. A significant 95% of all U.S. public company bankruptcies are captured in the high-risk red zone of scores. These are companies that filed for bankruptcy protection during the year after being scored by the model. We consider this to be an excellent, useful result.

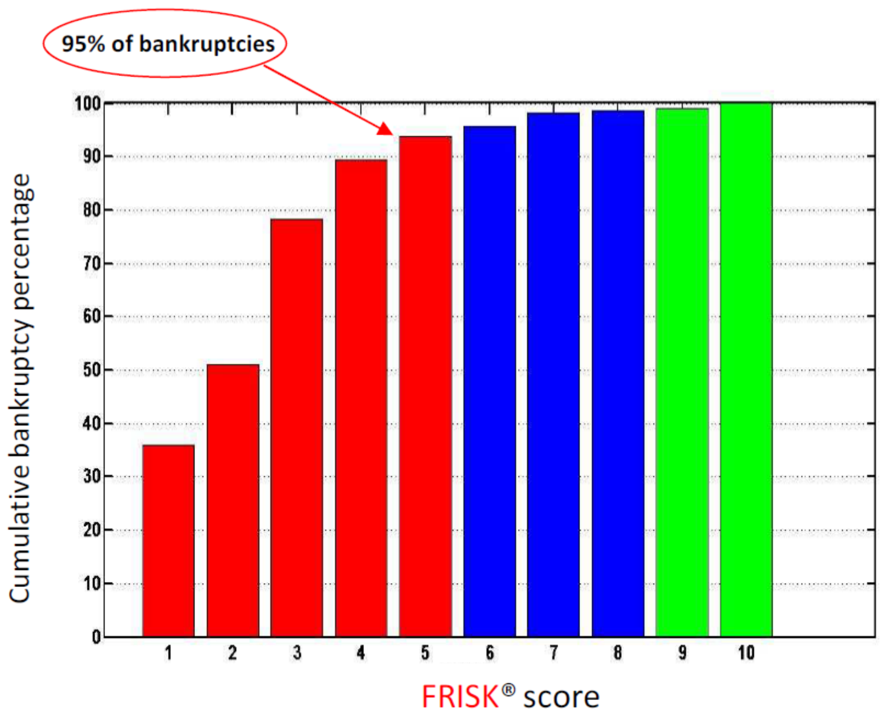

Figure 3. Showing the performance of the FRISK® score at identifying bankruptcies occurring in the subsequent 12 months. Scores "1" to "5" (red) are high-risk, capturing 95% of bankruptcies.

The graph in Figure 4 shows the average behavior of the FRISK® score for companies as they approach bankruptcy. The red area in the graph shows a range of average FRISK® scores for each month prior to bankruptcy[8]. The X-axis shows the range of scores from one month to 24 months prior to filing. As would be expected, the graph shows a strong negative trend: the range of scores generally continues to decline as companies get nearer to bankruptcy.

[8] The calculated FRISK® score mean is a sample mean and can change as different samples are taken. The vertical height of the blue curve is an indication of how much this mean can change over many company samples. It represents the 95% confidence level, meaning that we can expect 95% of sample means to be within the vertical range shown for any given month (X-axis).

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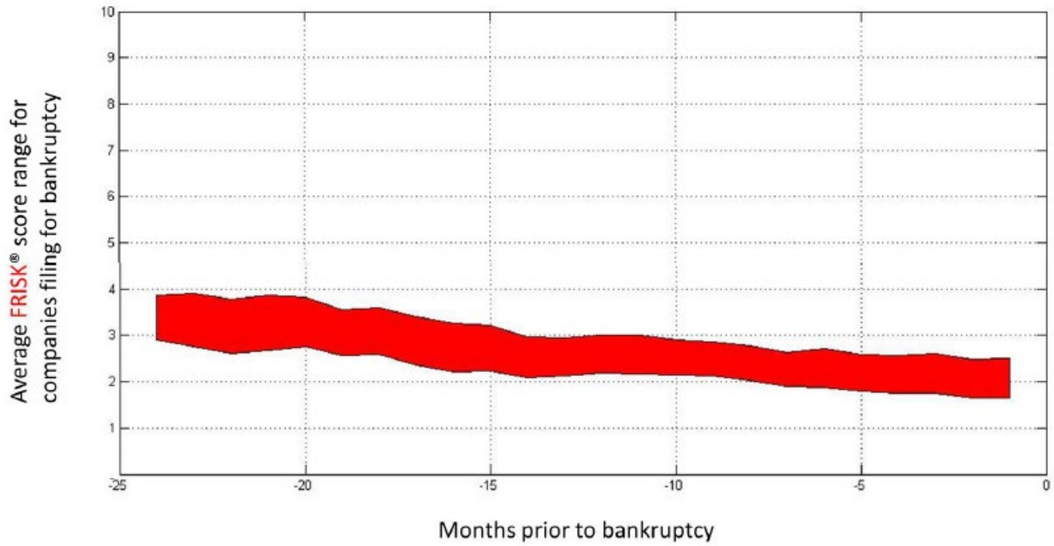

Figure 4. FRISK® scores for companies that actually go bankrupt are on average low & declining as bankruptcy nears (less than "4" at 24 months to "2" at filing).

Comparison of the FRISK® score with the Z"-Score

The Altman Z"-Score is a widely known and much used score to determine the financial strength of a subject company. The Altman Z"-Score formula uses just a few financial ratios, so it is easy to understand. However, because it only uses financial statement information (mostly balance sheet information) the Z"-Score is only updated when new financials are filed, so it is unable to reflect quick changes in the financial condition of a company. Also, the Z"-Score formula was created in 1974, and may not reflect the current accounting practices of public companies as well as it once did. Because it is so popular, it is often used as a benchmark for comparing financial risk scores.

The graph on Figure 5 shows an ROC graph comparing the effectiveness of the CreditRiskMonitor FRISK® score and the Z"-Score at identifying high-risk companies. It shows that the FRISK® score can be as much as three times more effective at a given level of misclassification error (FPR) than the Z"-Score. Note that this difference is especially important when an objective of using the score is to approve a large fraction of the companies analyzed (i.e., at low FPRs), as is typically true in Credit and Procurement. In addition, because the FRISK® score incorporates stock market information, it is also much more responsive to changes in financial condition than the Z"-Score.

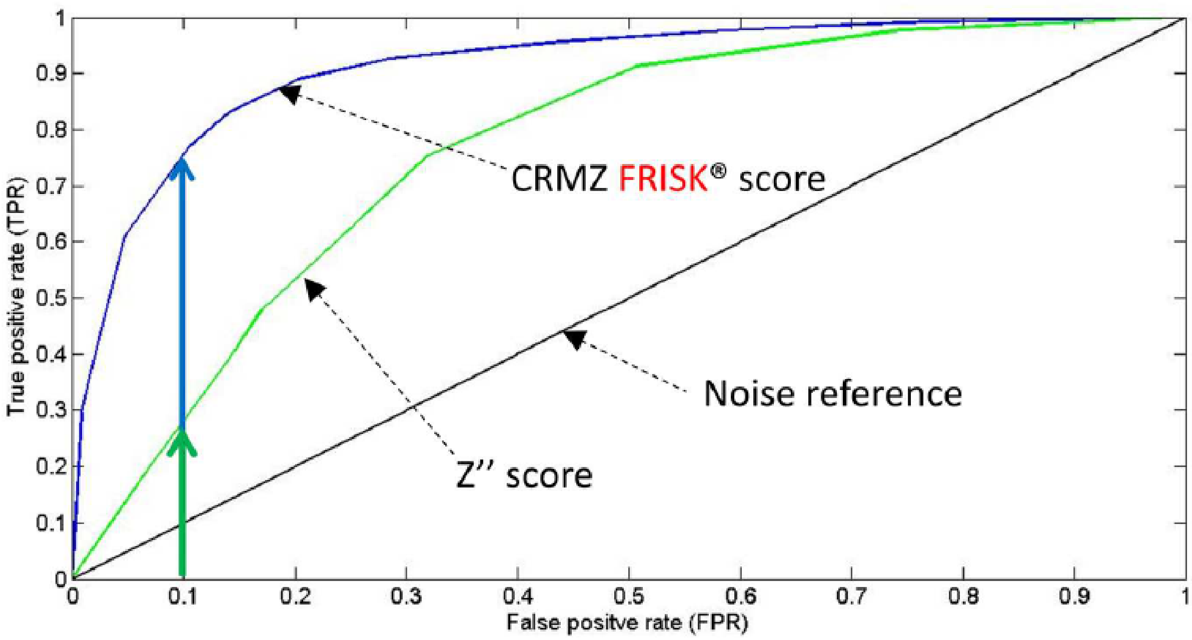

Figure 5. The ROC graph shows that the FRISK® score can be as much as three times more effective at identifying high-risk companies than the Altman Z"-Score.

Accuracy and timeliness can offer a Credit Manager or Procurement Analyst the opportunity to continue doing business with a company much longer, as its financial strength declines, without taking on significantly more risk. The Z"-Score may indicate the company is in severe financial distress years before it actually files for bankruptcy, if indeed it ever does go bankrupt. Ending a relationship too early is costly, and can appear foolish. Conversely, when a weak business' financial condition improves, the FRISK® score will typically show improvement sooner and can enable a sale on credit, or a purchase, with more confidence.

Conclusions

The CreditRiskMonitor service is designed for the needs of Credit and Procurement professionals. The FRISK® score is optimized for the needs of these professionals.

Credit and procurement professionals can use the CreditRiskMonitor FRISK® score to focus their attention and resources on the major problem businesses in their portfolio. The public companies covered by the FRISK® score are far fewer in number than private companies, but typically represent a very substantial fraction of the total dollars at risk, and so require definitive financial risk management.

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Unlike other modeling approaches, the FRISK® score is designed specifically for publicly traded companies, and uses multiple sources of data, combining (when available) stock market, financial statement and bond issuer rating information. This breadth of inputs enables the FRISK® to capture problem situations missed by other scoring models, and handle them more accurately. When compared to the popular Altman Z”-Score, the FRISK® score proved to be a much superior and timelier financial risk indicator.

Since it is an automated mathematical model, the FRISK® score is consistent and objective; it can also form the basis for further in-depth analysis of a troubled company. FRISK® scores are updated on a daily basis on over 30,000 companies worldwide, giving professionals the critical edge of early warning of coming financial stress for publicly traded companies worldwide as well as the opportunity to expand relationships as soon as financial strength returns.