Altman's Z-score and Option-based Approach for Credit Risk Measure
(Bankruptcy Prediction: Book value or Market Value?)

Abstract

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Based on our results, we learned that Altman's Z-score loses its significance as a bankruptcy prediction measure due to two possible grounds; it loses its prediction power for long-term prediction and it was not significance for recent years' data. In addition, we found that the option-based measure does provide significant results as a prediction measure for later years. We believe that the reduction of prediction time span of Z-score and better performance of the option-based measure implies that the more efficient market shortens the information transition time in the market so that bankruptcy prediction should be based on immediate and continuously changing information about the event and discrete or sporadic variables would mislay the interpretation of information concerning bankruptcy.

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Key words: Credit Risk Measure, Z-Score, Option, Default Prediction

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Introduction

Managers, stockholders, lenders and employees are concerned about their firm's financial condition. The job security of managers and employees is not assured should their firms struggle financially. Stockholders' equity position and lenders' claims are also not guaranteed. Government, as a regulator in a competitive market, has concerns about the consequences of financial distress for firms, and it controls capital adequacy through the regulatory capital requirement (Mingo, 2000). This shared interest among manager, employee, investor, and government creates continual inquiries and recurrent attempts to answer an incessant question about how we predict financial distress, or what reveals the credit risk of firms.

Despite numerous attempts to predict bankruptcy, three decades after Altman (1968)'s seminal study, financial distress prediction research has not reached an unequivocal conclusion. We believe that the lack of consensus in the study of financial distress prediction is partially attributable to the nature of the explanatory variables, as studied for three decades. Until Merton's (1974) proposal was applied to financial distress, most studies used financial ratios as explanatory variables, and the sole dependence on discrete types of variables was inevitable.

We assume that utilizing accounting-based variables from financial statements contains the following drawbacks:

First, being either less frequent, or discrete, accounting variables create a major impediment in predicting the probability of default, at a moment of interest prior to imminent financial distress. The frequency of accounting-based variables will be either quarterly or annual because they are obtained exclusively from quarterly- or annually-issued financial statements, i.e. from balance sheets or income statements. Therefore, the default probability of a firm will be unchanged for 12 months when a prediction is based on a certain year's annual financial statement (Altman and Saunders, 1998). In other words, no matter when we estimate the credit risk of a firm, the probability of bankruptcy is always identical during the given fiscal year because it is based on the same accounting variables, unless new or additional accounting information for the next fiscal year becomes available.

Second, the discreteness of financial statements restricts the scope of credit-risk measurement research. For instance, suppose we assume that increasing long-term debt financing changes the default probability of a corporation. We may proceed to measure the change of the bankruptcy probability, due to the specific event, exclusively based on accounting variables. However, we will not be able to extract the direct impact of this particular event by estimating a "quarterly" or "annual" change in credit risk because the result of credit risk estimation can be due to several other events that occurred during the same year, such as lawsuits against chief officers, change in interest rates, and a historical catastrophic event. Unless we have a continuous type of credit risk measure, the significance of statistical results from an event study becomes inevitably blurred by the intermittent or sporadic nature of accounting information concerning the possibility of default. A continuous variable would allow us to measure the change in bankruptcy immediately before and also after the event; such a variable would not only support the feasibility of an event study, but also eliminate the possibility of having mixed or confounding effects.

Third, financial statements fail to acknowledge the significance of a market mechanism in predicting bankruptcy because accounting variables are produced by a limited number of experts and accountants, but not by the market as a whole (Hillegeist et al., 2002). Reliance on less-frequent accounting data underestimates the notion that markets are a system of integrating information, and the stock price presents the dynamic exchange of information. Financial distress research with accounting variables assumes that an annual financial statement contains the necessary information to predict the financial soundness of a firm in the future. The stock market, however, aggregates investors' perceptions about the possibility of bankruptcy for a firm in the stock price, so that the market must be considered as a reliable resource in bankruptcy prediction. In addition, accounting information basically looks to the past, so that the probability of firms' vulnerability in the future can hardly be predicted with any accuracy.

In this paper, we attempt to reexamine the most commonly referred method in credit risk measurement research, Altman's Z-score model, by using recent bankruptcy data from 1996 to 2000. We investigate the five financial ratios in Altman's Z-score model in three respects: 1) the reduction of predictability of the Z-score for a longer prediction horizon, 2) the periodic change of predictability for years from 1996 to 2000, and 3) the applicability of the Z-score model to industries such as the Retail Trade industry and the Services industry.

We investigate how the predictability of five ratios changes as we forecast the bankruptcy of firms from longer than one year prior to the default, specifically from a 5-year prediction horizon to a 1-year prediction period. For the periodic change of 1-year predictability, we classify the bankruptcy data into five years in terms of its bankruptcy year and test if five financial ratios have been significant variables to the predict bankruptcy of firms one year prior to the bankruptcies. Also, we posit that Altman's Z-score was explicitly implemented as an industry-specific measure because Altman analyzed companies exclusively from the manufacturing sector. To evaluate the applicability of Altman's Z-score model to other industries, we test the one-year predictability of five ratios in the manufacturing, retail trade, and services industries, respectively, as well as all three industries in aggregate.

We postulate that the stock market has become more dynamic and integrated today than the market of the period when Altman's Z-score had significant predicting power for a firm's bankruptcy, with the consequence that Altman's Z-score model has lost its prediction power. We investigate recent literature to adopt a continuous type of default probability measure as an alternative prediction variable, and test its significance by using recent stock price data. The paper utilizes KMV's distance-to-default measure (henceforth, DD) as a proxy for bankruptcy, or default probability, to compare with independent variables in Altman's Z-score model. We test the significance of independent variables in the Z-score model (five financial ratios) and the option-based measure (the DD) by utilizing the logistic regression analysis for 1-year prediction from 1996 to 2000.

The comparison of two predictability models is made with respect to 1) the number of correctly classified bankruptcies by both models and 2) the Hosmer-Lemeshow test to assess the suitability of models (Hosmer and Lemeshow, 1989). The option-based model is not significant for all three industries as a whole, but it is consistently significant for the three individual industries, compared to the Z-score model, which is not significant for the manufacturing industry and the services industry. The reliability of the option-based measure for predicting the bankruptcies of manufacturing companies and retail trade companies is relatively high, 75% and 71%, respectively. However, the performance of the option-based measure for the service industry is not appealing because the possibility of correct classification is less than 50%. In conclusion, we find that Altman's Z-score model outperforms the option-based model for our data.

The paper begins with a literature review on the credit risk measure, followed by discussion on the option-based credit risk measure. The paper also describes the data collected, the variables analyzed and the statistical methods adopted in the paper. We conclude, after statistical results for the Altman's Z-score, and the comparison with the option-based measure are discussed.

Credit Risk Measurement Research

Research on credit risk measurement has been mainly focused on two issues: finding a reliable independent/explanatory variable, and statistical models with enhanced predictability[1].

The financial distress literature has been focused on finding explanatory variables that have discriminating power to differentiate financially distressed companies from financially sound companies, at least one year prior to bankruptcy. Initiated by Beaver (1966), Altman (1968), and Ohlson (1980), academic studies to measure financial vulnerability continued for three decades. Beaver found that the cash flow to debt ratio was the best single ratio predictor of distress in his univariate discriminant analysis. Altman's Z-Score model used multivariate discriminant analysis to select the five most significant variables for measuring the financial distress of firms[2]. Ohlson's O-Score model used a logit analysis to generate a one-year prediction model, and his academic descendants frequently referred to his discrete variables as a proxy for the probability of financial distress.

Altman (1968) collected data from 33 failed firms and 33 matching firms, during the period 1946-1965, to find discriminating variables for bankruptcy prediction. In his seminal paper, Altman evaluated 22 potentially significant variables of the 66 firms by using multiple discriminant analysis to build the discriminant function with five variables. The discriminant function is as follows:

$$Z = 0.012X_1 + 0.014X_2 + 0.033X_3 + 0.006X_4 + 0.999X_5,$$

,where $X_1 \equiv$ working capital/total assets, $X_2 \equiv$ retained earnings/total assets, $X_3 \equiv$ EBIT/total assets, $X_4 \equiv$ market value of equity/book value of total debt, and $X_5 \equiv$ sales/total assets.

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1 Refer to Altman and Saunders (1998) for literature review in detail.

2 The ratios are working capital/total asset, retained earnings/total assets, earnings before interest and taxes/total assets, market value of equity/book value of total liabilities and sales/total assets.

Altman finds that the prediction accuracy of the model tapers off for longer prediction horizons such as four- and five-year horizons. Accuracy tapers from 95% for 1-year and 72% for 2-year prediction horizon, to 48% for 3-year, 29% for 4-year and 36% for 5-year horizon.

Another stream of financial distress literature has been utilizing various statistical methods to predict the bankruptcy of firms. A few significant methods are: multinomial choice models such as logit and/or probit models (Martin, 1977; Santomero and Vinso, 1977; Ohlson, 1980; Zmijewski, 1984), multiple discriminant analysis (Altman, 1968), recursive partitioning (Frydman, Altman and Kao, 2002), neural networks (Altman, Marco and Varetto, 1994), and discrete hazard models (Hillegeist et al., 2002).

However, there is no consensus as to the best statistical model. For example, Back et al. (1996) studied 11 papers to reexamine 31 financial ratios by three distinctive statistical techniques: discriminant analysis, logit regression, and neural networks. Back et al. concluded that no consensus has been built on the best technique and the most significant explanatory variables.

No exclusive conclusion was found in a review of international applications of default prediction studies. The application of financial distress measurement literature flows into the international application of credit risk measurement to verify the robustness of such measures and techniques in different countries. Applying research on indicative variables and statistical methodologies internationally, Altman and Narayanan (1997) tried to identify financially stressed companies, but they concluded that no statistical method was consistently dominant.

Option-Based Credit Risk Measure

Several alternative approaches are based on option pricing models like Black and Sholes (1973) and Merton (1974). To be specific, Merton proposes that the equity value can be estimated as a call option on the market value of a firm's assets, which should be exercised only when the market value of the assets is greater than the value of liabilities of the firm.

Motivated by his study, subsequent research on financial distress measurement applies the European call option equation to find "the implied market value of assets (V_A)" from the following equity valuation equation. The equity valuation equation shows that its value is based on the market value of assets at time, the book value of liabilities, the time horizon, the risk free rate for the period, and the volatility of the market value of assets.

$$V_E = V_A N(d_1) - Ke^{-rT} N(d_2) ------------------- (1)$$

$$\text{, where } d_1 = \frac{\ln\left(V_A / X\right) + \left(r + \frac{\sigma_A^2}{2}\right)T}{\sigma_A \sqrt{T}},$$

$$d_2 = d_1 - \sigma\sqrt{T} \text{ and } N(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} e^{\frac{-y^2}{2}} dy$$

We can solve this equation for the implied market value of assets (V_A) if we can observe the following variables: the market value of firms' equity (V_E), the volatility of the market value of assets for the period of interest (σ_A), the risk free rate for the period (r), the point of time in the future where the default risk will be estimated (T), and the book value of liabilities of a firm at T (K)[3].

[3] K is calculated from the book value of liabilities of firms, and we examine different figures for K in the paper to test the significance of short-term debts and long-term debts in bankruptcy prediction. More detailed discussion follows.

Since we cannot observe the volatility of the market value of assets (σ_A) directly, we need to find an additional equation showing the relationship between the volatility of the equity (σ_E), market value of firm's equity (V_E), market value of firm's assets (V_A), and the volatility of the assets (σ_A) (KMV, 2002).

$$\sigma_E = \frac{V_A}{V_E} \Delta \sigma_A ---------------------- (2)$$

$$\text{, where } \Delta = N(d_1)$$

Now we are able to estimate the implied market value of assets, as well as the volatility of assets from two non-linear equations with two unknowns. Ronn and Verma (1986) utilized the option-based approach to price deposit insurance as a European put option[4]. Charitou and Trigeogis (2000) identified 139 firms that filed bankruptcy between 1983 and 1994, tested the significance of each variable in equation (1) independently, and tested some other accounting variables in terms of their discriminating power for the default probability of firms of interest. In Hillegeist et al. (2002), they found 516 bankruptcy filings between 1979 and 1997, and compared the risk-neutral default probability (which was adjusted with the firm's expected return on assets) to Altman's Z-Score and Ohlson's O-Score by introducing a unique discrete hazard methodology.

KMV used a similar approach to measure the default probability of firms. They postulate that "the default risk of the firm increases as the value of the assets approaches the book value of the liabilities, until finally the firm defaults when the market value of the assets is

[4] In their paper, "insuring a single, homogeneous-term debt issue against default of payment of principal and interest is equivalent to acquiring a European put option on the value of the bank before deposit insurance."

insufficient to repay the liabilities (p. 2, KMV 2002)." Their model calculates the DD (Distance-to-Default), $(V_A - K)/(V_A \cdot \sigma_A)$, and uses it as a proxy for a firm's credit risk. Since they built sufficient amounts of historic bankruptcy data, they were able to map this measure with historical default frequency data to estimate the default probability of the firm of concern. However, our research will be limited to adopting the KMV's Distance-to-Default (DD) in financial distress research in order to compare the bankruptcy predictability of DD with Altman's Z-score model.

We postulate that the market has become more integrated and dynamic, and that the flow of information through the stock price occurs very swiftly, and as a result, sporadic information such as the financial statement loses its expressive power in relation to a firms' financial condition. In addition, the market has become more accessible to investors due to more participation by individual investors, more transparent transactions among institutional investors, and higher levels of technological support to market participants. We hypothesize that the predictive power of the continuous-type of credit risk measure should have increased, compared to the discrete-type of credit risk measure. In other words, market participants are more capable of digesting information concerning the default probability of firms. As a consequence, the market-driven and continuous credit risk measure, as an aggregate indicator in the market, shall represent the enhanced trend of market development over time.

To use the credit measure suggested by KMV, we need to solve two non-linear equations with two unknowns — (1) and (2) — to estimate the implied market value of assets (V_A) and the implied annual volatility of a firm's assets (σ_A)[5]. Since the difference between the market

[5] Mathematica® is employed to solve the non-linear equation

value of assets and the firm's liabilities is divided by the market value of assets, this Distance-to-Default doesn't create any bias, due to the size of firms. Some explanations for estimation of each variable in two non-linear equations are necessary: We estimate the market value of equity (V_E) by multiplying the market value per share by the number of shares outstanding at the time of the bankruptcy prediction (i.e. market capitalization). The "1-year Treasury Constant Maturity Rates"[6] are collected as a proxy for risk free rates (r). The volatility of equity (σ_E) is computed from the standard deviation of daily returns on equity over the 1-year period prior to the bankruptcy date.

Most noticeably, the value of a firm's liabilities (K) is calculated, from five different combinations of short-term and long-term debts, to identify the significance of maturity of debts in a bankruptcy prediction. We know that lack of financial liquidity does most likely push the firm into the verge of financial distress and eventually force the firm to file a bankruptcy, unless the short-term financial difficulty is quickly dissolved. In the paper, we postulate that firms declare bankruptcy not only when they are unable to pay off their short-term debts but also when they hold significant amounts of long-term debts simultaneously. Even though the relative amount of short-term debts is the initial indicator showing the firm's financial distress, a firm eventually decides to declare bankruptcy when the relative amount of long-terms debts for assets is also too large.

Obvious cases are the short-term debts only, the long-term debts only, and the sum of short-term and long-term debts. In addition, we consider two more cases, in which short-term and long-term debts are considered disproportionately significant. We assign weights to short-

[6] Refers to "Yields on actively traded non-inflation-indexed issues adjusted to constant maturities," Federal Reserve Bank of St. Louis (http://research.stlouisfed.org)

term and long-term debts to test the impact of the maturity of debts on firms' financial distress. Those weights are 0, ½, or 1, and different pairs of weights are separately multiplied by short-term debts and long-term debts to create a "maturity-adjusted liability measure." For instance, if a pair of weights, ½ and 1, is assigned to short-term and long-term debts, the maturity-adjusted measure can be obtained simply by summing half of the short-term debts and the full amount of long-term debts. Five pairs of weights considered in the paper are as follows. Weights are (1, 0): Short-term debts only; (1, ½): Short-term and half of long-term debts; (1, 1): sum of short-term and long-term debts; (½, 1): long-term and half of short-term debts; (0, 1): long-term debts only. We adopt those five different approaches to calculate firms' liabilities for the option-based models.

Data and Statistical Methods

To examine the robustness of Altman’s Z-score model, we collected a list of companies having filed Chapter 11 during the period of interest. We identified 617 companies that filed Chapter 11 from 1996 to 2001 and were reported in Lexis-Nexis database (Table A).

Consulting with the Daily Return CRSP tape and the Annual Compustat files, we limited our sample to a group of companies listed in major exchanges in order to retrieve their historic stock price information as well as required accounting information for the period. In addition, we eliminated companies according to the following criteria: 1) we eliminated companies with less than five years of business history, to reduce the impact from early failure of startup companies; 2) we require at least two years of stock price information prior to bankruptcy because we are estimating the annual equity volatility by using the annual average of daily stock returns from two years prior to the Chapter 11 filing date; 3) companies which went bankrupt after year 2000 were dropped from a list of matching surviving firms so that the surviving period should be at least two years after the sampled firm’s failure; 4) we limit our analysis to the manufacturing , the retail trade, and the services industries; and 5) for each year, we look at the CRSP database to find a matching firm with similar size in terms of the market capitalization. Some failed companies are dropped when we cannot find a matching company because a prospective matching firm’s market capitalization is less than 50% or greater than 150% of the failed firm.

The table shows the number and the percentage of bankrupt firms that filed Chapter 11 for each year from 1996 to 2000 (Table B).

We chose the logistic regression as a statistical technique to test the significance of variables of interest in our study. For the Altman's Z-score model, we run multivariate logistic regressions for data, to reexamine the significance of the five financial ratios in Altman (1968)[7]. For the KMV model, we adopt the distance-to-default variable as an independent variable for financial distress prediction in the univariate logistic regression model. The following equation shows the generic form of the logistic regression model used in the paper.

$$\text{logic}(p) = \log\left(\frac{p}{1-p}\right) = X \Rightarrow p = \frac{e^X}{1+e^X} = \frac{1}{1+e^{-X}} \text{ ---------------(3)}$$

where

$$X = \beta_0 + \sum_{i=1}^{n} \beta_i x_i$$

, where $p =$ the probability of bankruptcy declaration, $\beta_0 =$ estimate of intercept, $\beta_i =$ coefficient estimate of five financial ratios in the Z-score model or the distance-to-default (DD) in the option-based model and $x_i =$ each financial ratio or the distance-to-default

Our statistical analyses consist of two parts: testing the significance of the regression model, and testing the significance of individual variables. In "Testing the Global Null Hypothesis: Beta=0," we test three different chi-square statistics: Likelihood, Score, and Wald. Those statistics are calculated to test the following null hypothesis that all the explanatory variables have coefficients of zero.

$$\mathrm{H}_0 : \beta_0 = \beta_1 = \beta_2 = \beta_3 = \beta_4 = \beta_5 = 0 \quad \text{--------------(4)}$$

[7] For both analyses, the ratios are working capital/total assets (WC/TA), retained earnings/total assets (RE/TA), earnings before interest and taxes/total assets (EBIT/TA), market value of equity/book value of total liabilities (MVE/BVTL) and sales/total assets (Sales/TA).

If the corresponding p-value is less than a significance level (α), we reject the null hypothesis and conclude that at least one of the coefficients is not zero. If we cannot reject the null hypothesis, we conclude that all of them are zero and the model is not significant as a financial distress prediction model.

Next, in "Analysis of Maximum Likelihood Estimates," we find coefficient estimates and p-value for Wald chi-squares to test the null hypothesis that each coefficient estimate is zero.

$$H_0 : \beta_i = 0 \quad \text{---------------(5)}$$

We reject the null hypothesis that each corresponding coefficient is equal to zero if a p-value is less than a significance level (α), and conclude that the corresponding independent variable has a significant discriminating power for firms' financial distress.

Statistical Results

Altman's Z-Score Model

The paper investigates the robustness of Altman's Z-score model. The tests for the Z-score model are performed under our supposition that the Z-score model has lost its significance as a prediction model because the market has become more integrated and dynamic and, as a result, the discrete and sporadic accounting variables used in the model have become rather obsolete. Three aspects of predictability of the Z-score model are tested. First, we test the significance of the model in terms of the prediction horizon, because we believe that the Z-model has lost its predictability for longer horizons, for instance, longer than 2 years. Second, we test the significance of the Z-score model from 1996 to 2000 because we hypothesize that the model has gradually lost predictability due to the change of market dynamics and integration of markets. Lastly, we test the significance of the model for individual industries because we propose that the Z-model was developed as an industry-specific measure, particularly the manufacturing industry sector, and that the model is not appropriate to a certain other industry, such as an industry in the service industry sector.

We limit our analysis to logistic regression analysis because our contribution is focused on comparing discriminant variables in the Z-score model and an option-based approach[8].

Horizon of Predictability

In Altman (1968), he shows that the predictability decreases from 95% for 1-year prediction to 48% for 3-year prediction and stays low. In this paper, we are motivated to replicate his analysis to reexamine the significance of variables in Z-score model for longer horizons so that we can limit our further analyses only on the statistically significant prediction horizons. We postulate that Altman's Z-score model has lost its predictability for longer prediction horizons because we propose that the transition of information in the market has become swift and instantaneous and that accounting variables do not represent the most current information. We utilize the logistic regression to examine whether the model can provide considerable discriminating power for bankrupt firms of all three industries from 1996 to 2000.

We test the predictability of the Z-score model from five years to one year prior to bankruptcies. We have the following logistic model to test the global null hypothesis. Results from the logistic regression on all three industries, to test the change of predictability for different horizons, is shown in Table C.

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[8] As an advantage of using the logistic regression, we are free from the multivariate normality assumption among independent variables.

$$\text{logic}(p_h) = \log(\frac{p_h}{1-p_h}) = X_h \Rightarrow p_h = \frac{e^{X_h}}{1+e^{X_h}} = \frac{1}{1+e^{-X_h}} \text{ for each horizon } (h) \text{ - - - - - - - - - -(6)}$$

where p_h = bankrupty probability for h year(s) prior to bankruptcy,

$X_h = \beta_{0,h} + \beta_{1,h}x_{1,h} + \beta_{2,h}x_{2,h} + \beta_{3,h}x_{3,h} + \beta_{4,h}x_{4,h} + \beta_{5,h}x_{5,h}$, where.

$x_{1,h} \equiv$ Working capital / Total assets , $x_{2,h} \equiv$ Retained earnings / Total assets,

$x_{3,h} \equiv$ EBIT / Total assets, $x_{4,h} \equiv$ Market value of equity / Book value of total debts,

$x_{5,h} \equiv$ Sales / Total assets, for $h = 1$ to 5,

* All ratios are collected h year(s) prior to bankrutpcy from 1996 to 2000

Three chi-square statistics, Likelihood, Score and Wald, in the logistic regression table show the result from the test of the global null hypothesis, postulating that none of independent variables in the model are related to changes in probability of bankruptcy occurrence.

$$\text{H}_0 : \beta_{0,h} = \beta_{1,h} = \beta_{2,h} = \beta_{3,h} = \beta_{4,h} = \beta_{5,h} = 0 \text{ for each horizon } (h) \text{ - - - - - - - - - - -(7)}$$

, where $h = 1$ to 5 from 1996 to 2000.

For aggregate data of all three industries, the Z-score model is significant and the global null hypothesis is rejected at $\alpha = 0.01$ level for up to three leading years so that we can state that at least one of the coefficient estimates is not zero, at 1% significance level. As a result, a bankruptcy can be predicted for less than four leading years prior to bankruptcy from the Z-score model.

For years between 1996 and 2000, all variables in Altman's Z-score model do not always explain the bankruptcy of firms in three industries. For each prediction horizon, from 5-year to 1-year prior to bankruptcy, we find the coefficient and p-value for chi-square statistics to test the following null hypothesis.

$$H_0 : \beta_{i,h} = 0 \text{ for each i and } h \text{ --------------(8)}$$
$$\text{, where i} = 0 \text{ to } 5 \text{ and } h = 1 \text{ to } 5$$

For those three different prediction horizons (1, 2, and 3 years), "Working capital/Total assets" seems to be a consistently significant predicting variable for at least three years prior to bankruptcy. For a 1-year prediction horizon, which is the most significant model, only two additional independent variables are significant at $\alpha = 0.01$. For the immediate prediction, "EBIT/Total assets" and "Market value of equity/Book value of Total Liabilities," in addition to "Working capital/Total assets," can be considered as significant bankruptcy indicators. Since the relationship between the market value of stock and the book value of liabilities is a significant prediction variable for one year prediction horizon, it is consistent with our proposition that our bankruptcy prediction studies should be restricted to market-related variables.

We also investigate the "Max-rescaled R-square" to see what portion of data is explained by the logistic regression model (SAS, 2001)[9]. Apart from the one-year prediction horizon model, it is difficult to state that the Z-model fits the data. Only one-year prediction horizon model shows the Max-rescaled R-square of 0.6132, which means that 61.32 percent of data can be explained by the model when we use the Z-score model to predict the bankruptcy of a firm, one year from today.

Hence, the Z-score model seems to be reasonable predictor of the financial distress of firms just one-year prior to bankruptcy, but it should be done with the caution that some

[9] To fix a possible drawback of the generalized R^2 of having an upper bound is less than 1 due to dicrete dependent variables, the division of the original R^2 by its upper bound gives the "Max-rescaled Rsquare."

variables would be insignificant. Our estimation of the Z-score model turned out to be less satisfactory than Altman's original results, for longer prediction horizons.

Change of Predictability

We evaluate whether the predictability of the Z-score model has been changed to uphold the test of time so that the model produces reliable predictability for recent years (Table D). Since we find that using the Z-score model for a prediction of a bankruptcy for longer than one year is not significant, we focus our analysis on a 1-year prediction horizon to test the change of predictability of the Z-score model. We show the following logistic regression model to test the change of predictability of 1-year prediction of the Z-score model in 1996 to 2000.

$$\text{logic}(p_y) = \log\left(\frac{p_y}{1-p_y}\right) = X_y \Rightarrow p_y = \frac{e^{X_y}}{1+e^{X_y}} = \frac{1}{1+e^{-X_y}} \text{ for each year}(y) \text{---------} (9)$$

where p_y = bankrupty probability 1 year prior to bankruptcy in year y, and

$X_y = \beta_{0,y} + \beta_{1,y}x_{1,y} + \beta_{2,y}x_{2,y} + \beta_{3,y}x_{3,y} + \beta_{4,y}x_{4,y} + \beta_{5,y}x_{5,y}$, where.

$x_{1,y} \equiv$ Working capital / Total assets, $x_{2,y} \equiv$ Retained earnings / Total assets,

$x_{3,y} \equiv$ EBIT / Total assets,

$x_{4,y} \equiv$ Market value of equity/ Book value of total debts

$x_{5,y} \equiv$ Sales / Total assets, for $y = 1996$ to 2000.

* All ratios are collected 1 year prior to bankrutpcy for bankruptcies in year y,

From the first glance at Table D, the Altman's Z-score seems to be a significant model because three chi-square statistics for the following global null hypothesis are significant at $\alpha = 0.01$ and max-rescaled R-squares are very high. However, we can also notice that the max-rescaled R-squares have decreased from 0.9988 in 1996 to 0.6266 in 2000, except for 1998.

$$\mathrm{H}_0 : \beta_{0,y} = \beta_{1,y} = \beta_{2,y} = \beta_{3,y} = \beta_{4,y} = \beta_{5,y} = 0 \text{ for each year } (y) \text{ -------(10)}$$
$$\text{, where } y = 1996 \text{ to } 2000$$

The results partially confirm our postulation that the market may become more responsive to the flow of information, but we cannot conclude that the Altman's Z-score model has lost its predictability for one-year horizon for 1996-2000 because the result for 2000 should be considered as an exception rather than a trend. We find that only one independent variable in 1998 (WC/TA) and two independent variables (WC/TA and MVE/BVTL) are significant for bankruptcies from the following null hypothesis tests.

$$\mathrm{H}_0 : \beta_{i,y} = 0 \text{ for each i and year } (y) \text{ -------------(11)}$$
$$\text{, where i} = 0 \text{ to } 5 \text{ and } y = 1996 \text{ to } 2000$$

Industry Dependency

We want to see whether or not the Z-score model is an industry-specific model (Table E). Since sampled companies in the paper were manufacturing companies when the Z-score model was initially introduced in Altman (1968), the Z-score model might be able to predict the bankruptcy of manufacturing firms with reasonable accuracy. We conjecture that the Z-score model will be less significant in predicting recent years' bankruptcy for other industries. Since the proportion of manufacturing companies in the economy has declined, the decline in the performance of the Z-score can be attributed to the structural change of industries in the economy. We also use the logistic model for the industry-specific prediction model.

$$\text{logic}(p_g) = \log(\frac{p_g}{1-p_g}) = X_g \Rightarrow p_g = \frac{e^{X_g}}{1+e^{X_g}} = \frac{1}{1+e^{-X_g}} \text{ for each group } (g) \text{ - - - - - - - - -} (12)$$

where

p_g = bankrupty probability 1 year prior to bankruptcy in industry group g ,

$X_g = \beta_{0,g} + \beta_{1,g}x_{1,g} + \beta_{2,g}x_{2,g} + \beta_{3,g}x_{3,g} + \beta_{4,g}x_{4,g} + \beta_{5,g}x_{5,g}$, where.

$x_{1,g} \equiv$ Working capital / Total assets ,

$x_{2,g} \equiv$ Retained earnings / Total assets,

$x_{3,g} \equiv$ EBIT / Total assets,

$x_{4,g} \equiv$ Market value of equity / Book value of total liabilities

$x_{5,g} \equiv$ Sales / Total assets, for $g \equiv$ manufacturing, retail trade and services.

* All ratios are collected 1 year prior to bankrutpcy for bankruptcies in year 1996 - 2000,

Rejection of the following global null hypotheses in the Z-score model for three industries shows evidence that the Z-score model can be used for the prediction of bankruptcies one-year prior to the event.

$$H_0 : \beta_{0,g} = \beta_{1,g} = \beta_{2,g} = \beta_{3,g} = \beta_{4,g} = \beta_{5,g} = 0 \text{ for each group } (g) \text{ - - - - - - -} (13)$$

, where g = manufacturing, retail trade and services

In addition, Max-rescaled R-squares for the three industries are relatively high, 0.63, 0.7856 and 0.5322, respectively, so that we can, with relative accuracy, predict bankruptcy in those three industries with the Z-score model as long as we want to predict for bankruptcy one year prior to a bankruptcy. However, it may be less accurate for us to predict a bankruptcy for a firm in the services industry because the Max-rescaled R-square is only 0.5322 for the industry.

We also investigate the significance of independent variables as bankruptcy prediction variables by testing the following null hypothesis.

$\mathrm{H}_0 : \beta_{i,g} = 0$ for each i and g -------------(14)

, where i = 0 to 5 and g = manufacturing, retail trade and services

The results are very similar to the results for the manufacturing industry sector, and are similar to the results for the aggregate data. RE/TA and Sales/TA are never significant and WC/TA, EBIT/TA and MVE/BVTL are significant variables for one-year prediction, but not all three industries. Only EBIT/TA and MVE/BVTL are significant prediction variables for the retail trade industry, and MVE/BVTL is the only significant variables for the services industry. Therefore, from the null global hypothesis tests, we find that the Z-score model on average is a reliable bankruptcy prediction model, however we should consider an improvement of the model based on considering different independent variables or an alternative model.

In summary, from the global null hypothesis analyses of Altman's Z-score, we learned that variables in the Z-score model have lost the significance more as a bankruptcy prediction measure for longer than 1-year horizons. And the predictability of the model has gradually, but not significantly, decreased. We note that predictability is higher for the retail trade industry and we conclude that it should be used with limitation for some industries. From independent variable analyses, we note that "Sales/Total Assets" is never significant for any industry or any year, and "Market value of equity/Book value of Total Liabilities" is the most significant ratio among five ratios for default prediction analysis.

Comparison of Z-score model and Option-Based Model

The option-based measure in our paper (i.e. Distance-to-Default) is analyzed to answer our inquiries: 1) whether the option-based model provides us with a better or more significant prediction model than the Altman's Z-score model; 2) whether the option-based model provides significant analysis outcomes for other industries or whether the option-based model is industry-specific; and 3) whether short-term debts or long-term debts force a firm to declare bankruptcy, or whether relative weights between short-term liabilities and long-term liabilities should be considered for prediction.

We use the logistic regression to compare the following model for the option-based model with the Z-score model.

$$\text{logic}(p) = \log\left(\frac{p}{1-p}\right) = X \Rightarrow p = \frac{e^X}{1+e^X} = \frac{1}{1+e^{-X}} \text{ - - - - - } (15)$$

$$X = \beta_0 + \beta_1 x_1$$

, where $p =$ bankrupty probability for 1 - year prior to bankruptcy and $x_1 \equiv \text{DD}$

We answer the first inquiry by analyzing proportions of cases correctly classified by each model for one-year prediction in terms of two categories: the Hosmer and Lemeshow goodness-of-fit test, and the Classification table.

The Hosmer-Lemeshow calculates predicted probabilities for all observations which are sorted by size into approximately 10 intervals. For each interval, the expected frequency is obtained by adding up the predicted probabilities. Expected frequencies are compared with observed frequencies by the conventional Pearson chi-square statistic. Hosmer and Lemeshow provide a chi-square test to determine how well the data under analysis perform under the null hypothesis that the model fits the data.

The classification table shows the number of correctly classified data based on the model when a certain probability level of having an event happened is assigned, such as 25%, 50% and 75% in our analysis.

Based on those two criteria, the Altman's Z-score proves to be a better model than the option-based model for the aggregate data of three industries (Table F). For the option-based model, the null hypothesis that the model fits the data is rejected at the $\alpha = 0.01$ significance level, and only 67.5% of the data are correctly classified into a group of bankrupt firms when the model is used to classify a group of firms with the 25% probability level of being bankrupt, compared to 79.7% level with the Z-score model. The Altman's Z-score model outperforms the option-based model even with the probability level of 50% and 75%. It allows us to assert that the Altman's Z-score model is still a better model to predict the chance of defaults of firms within a year, compared to the option-based model based on the study for recent years' bankruptcies.

When we compare the predictability of the Altman's Z-score model and the option-based model for individual industries, we find that the Altman's Z-score model's predictability is reliable only for the retail trade industry. For other two industries, Hosmer and Lemeshow's chi-square test for the Z-score model rejects the null hypothesis that the model fits the data. Combined with the result on the predictability of the Z-score model for the aggregate data, we find that the Z-score model shows that it is an industry-specific measure because it outperforms the option-based model for the aggregate data of three industries but fails to beat the option-based measure for the manufacturing industries and the services industries when they are separately analyzed. The Z-score model fails to provide consistent results for individual industries. We infer that its superior predictability for the retail trade industry sector may inflate the limited significance of the model for the manufacturing and the services industries. In contrast, the option-based model proves to be a consistently significant method for all three industries because all null hypotheses are not rejected.

However, we use caution on the second criteria for our comparison. The Z-score model outperforms the option-based measure in all three industries when we examine the number of correct classifications by both models. The Altman's Z-score model can classify defaults of retail trade companies at 82.1% when we look for firms which have 25% probability of being bankrupt in a year. Apart from the fact that the Z-score model does not fit the data, it correctly classifies defaults of firms in the manufacturing industry at 79.1% and in the services industry at 64.5%, respectively.

For our comparison analysis, we use five different combinations of short-term debts and long-term debts as a proxy for a firm's liabilities (K) in the equation to examine whether the liquidity constraint from short-term liabilities alone actually forces firms to declare bankruptcy, or if we should consider that the amount of long-term debts is also relevant to determining a firm's bankruptcy probability. As shown in Table G, we find that defaults of firms in different industries should be attributable to different leverage conditions of firms. The short-term debts can be considered an exclusively significant indicator for firms' default in the manufacturing industry sector. An equal amount of attention should be paid to the short-term debts and the long-term debts in the retail trade industry sector, while the short-term debts are slightly more important in predicting a default of firms in the service industry sector.

Concluding Remarks

Our postulation concerning Altman's Z-score and the option-based measure is based on arguments that the Z-score should lose its significance since its introduction, due to following reasons. First, the Z-score measure should lose its predictability for other industries because the Z-score was originally designed to predict the default of manufacturing companies; expansion of the application to the service industry dilutes the significance of the model for recent years. Second, the discrete type of measure, such as financial ratios, should be replaced with the continuous type of measure, such as the option-based measure, so that the financial impact of any event can be examined using continuous measure.

Based on results, we learn that Altman's Z-score model may have partially lost its significance as a bankruptcy prediction measure on two grounds: it is losing its prediction power for long-term prediction, and its accuracy is deteriorating for recent years' data. However, we fail to assert that the option-based model performs better than variables in Altman's Z-score model even though we find that the option-based measure provides significant results as a 1-year prediction measure for recent years in individual industries.

In summary, the Z-score model still produces more consistent results for the data collected and analyzed in terms of the "Max-rescaled R-square" and the "Classification Table" and seems to be more reliable than the option-based model due to its higher classification rate. However, we cannot eliminate the possibility of modifying the option-based model because it produces consistently better results in the "Goodness-of-Fit" test. Even though the option-based model remains as an opportunity for us to adopt the option-based measure into areas of finance, it is worthwhile to mention the applicability of the measure for future research.

The measure creates a significant impact on other finance research since its ability to test existing hypotheses with the new continuous variable may hold promise for a new stream of studies. Workable and promising topics with the new credit risk measure are not limited to the following examples.

First, we want to use the option-based default probability as a proxy for predicting the bankruptcy risk or credit risk of corporations, and apply it to corporate literature. We may be able to suggest a clue for the dividend puzzle by finding a relationship between dividend payout policy and the firm's default probability. Many scholars have strived to explain the reasoning behind firms' dividend payment policy so that they can provide a description of how firms decide between dividend payout and share repurchase. Using this new continuous/distinctive variable, we test if payout policy signals the change of credit risk in a firm, and if there is any significant difference, in terms of default probability, before or after changes in payout policy. We posit that firms' managers prefer dividends payout to share repurchase because it increases the risk of projects on behalf of existing shareholders and themselves.

Second, we can investigate the impact of catastrophic events by measuring change in the overall default probability of firms after the event. Because of increasing individual investor participation and enhanced market transparency in the recent market, we believe that the continuous type of credit risk measure has higher predictive or discriminant power to identify financially distressed firms, one year prior to the bankruptcy. This credit risk measure helps to estimate financial impact in different industries, for instance, after momentous events such as

September 11, so that we can define which industries are more vulnerable to certain fundamental risks. We can measure the change in aggregate credit risk for different industries so that we can determine which industry is most vulnerable to a particular event. We believe that our study can easily extend this approach to test the financial impact of different events in a specific industry sector.

Even though the option-based measure supplies an alternative prediction tool for scholars and practitioners, we failed to provide evidences that the option-based model is a better predictor than variables in Altman's Z-score model so that we should conclude our paper with one necessary caution. As we found, the measure is applicable only to a certain industry, such as manufacturing and retail trade in our study, and the possibility of modification of the measure remains promising but challenging.

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Appendix

Table A: Industry and Number of Chapter 11 Filings		
A	Agriculture, Forestry, & Fishing	3
B	Mining	31
C	Construction	9
D	**Manufacturing**	**188**
E	Transportation, Communications, Electric, Gas & Sanitary Services	70
F	Wholesale Trade	33
G	**Retail Trade**	**117**
H	Finance, Insurance & Real Estate	56
I	**Services**	**107**
J	Public Administration	3
	Total	**617**

Table B: Selected Bankrupt Companies in 1996 to 2000

Year	Frequency	Percentage
1996	14	12.6%
1997	11	9.9
1998	23	20.7
1999	27	24.3
2000	36	32.4
Total	**111**	100.00

Table C: Logistic Regression on Z-Score's Predictability of Horizons

					Industries					
	5-year Horizon		*4-year Horizon*		*3-year Horizon*		*2-year Horizon*		*1-year Horizon*	
Testing Global Null Hypothesis										
Test:Beta=0	ChiSq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq
Likelihood	10.7331	0.0569*	5.2055	0.3913	17.9839	0.0030**	23.6869	0.0002**	123.9817	0.0001**
Score	9.2968	0.0978*	5.0483	0.4100	15.5557	0,0082**	19,5988	0.0015**	54.6273	0.0001**
Wald	8.7079	0.1213	4.7267	0.4501	13.1886	0.0217**	17.5183	0.0026**	38.4121	0.0001*
Analysis of MLE										
Coefficients	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq
Intercept	0.3352	0.3997	0.4230	0.2188	0.4286	0.2141	0.6192	0.0731*	1.0868	0.0090**
WC/TA	-1.0484	0.1590	-0.3672	0.5073	-1.6740	0.0104**	-2.6510	0.0001**	-1.7228	0.0561*
RE/TA	-0.4810	0.3065	0.2534	0.3525	-0.2532	0.5260	0.1733	0.6117	-0.3653	0.3811
EBIT/TA	-2.1292	0.1162	-1.4821	0.1515	-0.3430	0.7841	-1.6848	0.1535	-6.1059	0.0013**
MVE/BVTL	-0.0024	0.8535	-0.0236	0.1809	-0.0134	0.4448	0.0080	0.6409	-1.2220	0.0001**
Sales/TA	0.2257	0.2891	-0.0621	0.7443	0.0780	0.6765	0.0291	0.8775	0.0240	0.9053
Max-rescaled R-Square										
		0.0683		0.0315		0.1033		0.1355		0.6132

**Significant at 0.05 level and **Significant at 0.01 level*

Table D: Logistic Regression on Change of Z-Score's Predictability

	1996		*1997*		*1998*		*1999*		*2000*	
Testing Global Null Hypothesis (1-year Predictability)										
Test:Beta=0	ChiSq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq
Likelihood	19.3967	0.0016**	37.5275	0.0001**	40.5249	0.0001**	34.2594	0.0001**	31.3057	0.0001**
Score	10.3646	0.0655*	17.3564	0.0039**	13.1406	0.0221**	16.1878	0.0063**	15.4568	0.0086**
Wald	0.2683	0.9982	6.8507	0.232	2.8901	0.7169	10.9411	0.0526*	4.4069	0.4924
Analysis of MLE										
Coefficients	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq
Intercept	21.1348	0.7275	3.8810	0.0647*	2.3561	0.6467	0.2983	0.9882	1.1441	0.4555
WC/TA	-24.6073	0.9150	-8.1552	0.1444	15.2717	0.5033	-4.8153	0.0146**	0.0731	0.9735
RE/TA	-7.5833	0.9651	-2.5095	0.3634	-30.6906	0.1627	0.8892	0.2830	-2.7102	0.3028
EBIT/TA	-6.8476	0.9780	-9.0726	0.3129	-101.90	0.1748	-3.9241	0.3018	-8.8115	0.1710
MVE/BVTL	-8.1441	0.7122	-2.0727	0.0275**	-19.5108	0.1585	-2.0385	0.0082**	-3.8881	0.1772
Sales/TA	-2.8250	0.9483	0.3084	0.7718	1.0506	0.6967	1.4650	0.1193	-0.8530	0.3907
Max-rescaled R-square										
		0.9988		0.9997		0.8116		0.9681		0.6266

**Significant at 0.05 level ** Significant at 0.01 level*

Table E: Logistic Regression on Z-Score's Industry–Specific Predictability (1-year prediction horizon)

Testing Global Null Hypothesis (1-year Predictability)	***Manufacturing***		***Retail Trade***		***Services***	
Test:Beta=0	ChiSq	Pr>ChiSq	Chi-Sq	Pr>ChiSq	Chi-Sq	Pr>ChiSq
Likelihood	73.4203	0.0001**	49.5125	0.0001**	15.6106	0.0090**
Score	34.7688	0.0001**	22.0369	0.0005**	9.8282	0.0803*
Wald	23.2941	0.0003**	7.3006	0.1992	6.1113	0.2955
Analysis of MLE						
Coefficients	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq	Estimate	Pr>ChiSq
Intercept	1.5395	0.0422**	2.3452	0.0788*	1.7604	0.1846
WC/TA	-2.9561	0.0263**	-0.5612	0.7924	-0.3119	0.9220
RE/TA	-0.2750	0.5777	-2.3479	0.1599	0.4561	0.7449
EBIT/TA	-4.3748	0.0508*	-19.6911	0.0362**	-11.7034	0.1318
MVE/BVTL	-1.0440	0.0003**	-3.9442	0.0420**	-0.8380	0.0740*
Sales/TA	-0.0330	0.9507	-0.1811	0.5813	-1.1088	0.3212
Max-rescaled R-square						
		0.63		0.7856		0.5322

**Significant at 0.05 level ** Significant at 0.01 level*

Table F: Comparison of Z-score and Option-based Model (Three Industries)

	Z-score Model			**Option-Based Model**		
Hosmer and Lemeshow Goodness-of-fit Test						
	Chi-Square	DF	Pr>Chi-Sq	Chi-Square	DF	Pr>Chi-Sq
	8.0175	8	0.4318	32.8859	8	0.0001**

Classification Table

Probability Level	Correct	Correct
0.25	79.7	67.5
0.5	84.2	75.1
0.75	74.3	63.3

***Significant at 0.01 level*

Table G: Comparison of Z-score and Option-based Model for one-year prediction horizon

Manufacturing

	Z-score			Option-Based [(s,l)=(1,0)]		
Hosmer and Lemeshow Goodness-of-fit Test						
	Chi-Square	DF	Pr>Chi-Sq	Chi-Square	DF	Pr>Chi-Sq
	46.7444	8	0.0001**	12.8481	8	0.1172
Classification Table						
Probability Level	Correct			Correct		
0.25			79.1			74.7
0.5			87			80.8
0.75			78.3			64.6

Retail Trade

	Z-score			Option-Based [(s,l)=(1,1)]		
Hosmer and Lemeshow Goodness-of-fit Test						
	Chi-Square	DF	Pr>Chi-Sq	Chi-Square	DF	Pr>Chi-Sq
	2.2336	8	0.897	6.3276	8	0.6106
Classification Table						
Probability Level	Correct			Correct		
0.25			82.1			70.8
0.5			75			68.8
0.75			78.6			66.7

Services

	Z-score			Option-Based [(s,l)=(1,1/2)]		
Hosmer and Lemeshow Goodness-of-fit Test						
	Chi-Square	DF	Pr>Chi-Sq	Chi-Square	DF	Pr>Chi-Sq
	16.903	8	0.0311*	6.8811	8	0.6495
Classification Table						
Probability Level	Correct			Correct		
0.25			64.5			45.5
0.5			64.5			50
0.75			64.5			40.9

***Significant at 0.01 level*