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D-Score: Bankruptcy Prediction Model for Middle Market Public Firms

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ABSTRACT:
This paper addresses theoretical and practical issues underlying bankruptcy prediction. By using the latest data on middle market publicly traded companies it estimates a model in accordance with the Gambler's Ruin and Merton models with a forward selection process. The model's empirical performance is encouraging, but for better validation needs further testing on larger samples of companies not used in the initial estimation of the model.

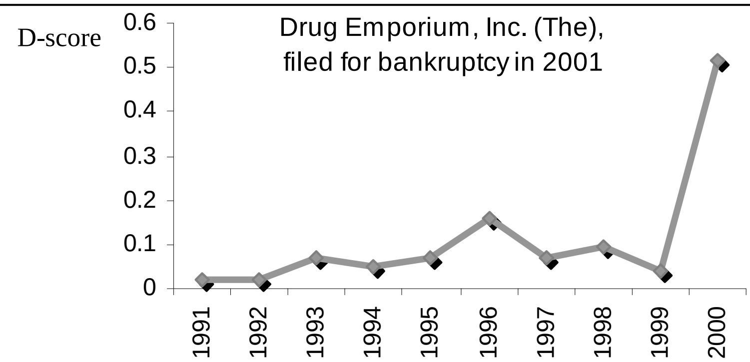
Capitalism without bankruptcy is like Christianity without Hell.
Frank Borman

1. Introduction[1]

Proponents of Schumpeter's *Creative Destruction* argue that the existence of bankruptcies is a necessary evil, and yet a costly one. The ability to predict bankruptcy can be greatly utilized in such situations as business loan evaluations, internal performance assessment, and identifying undesirable investments/desirable targets for short-trading to name a few. The question then is how can one recognize a company that will go bankrupt? A considerable amount of research has been conducted on this subject with variable success. Even though bankruptcy statistical models were introduced more than 30 years ago, the middle and lower market bankruptcy assessment is still primarily a subjective process. There are no widely accepted benchmarks for this procedure.

In sharp contrast, consumer lending has experienced an incredible advance to the point where ones credit experience can be measured with 90% certainty. For the most part this is attributed to the sample size. Consumer bankruptcies reach into the hundreds of thousands while the non-bankrupt cases run into the millions. This paper develops a model (D-Score coming from distressed) that can be used as an *objective check* to assess the probability of bankruptcy for middle market publicly traded companies. The model is estimated on the most recent data, is easy to use and utilizes data that is readily available.

Chart 1: D-Score out-of-sample performance (anecdotal evidence)



Drug Emporium was a leading deep discount retailer of brand name health and beauty care items, over-the-counter medications, prescription drugs, greeting cards, cosmetics, vitamins and consumable products. Steep price competition and some internal turmoil caused the company to file for protection under Chapter 11. (*Source: SB Capital Group, press release*)

[1] I would like to thank Gary Krueger for guidance and assistance throughout the project and Weiwen Miao, Tanzeen Syed, Bibek Raj Pandey, Irina Asmalova, Marius Hansen, John Lentz, Melanie Roberts, Dan Flath for their helpful advice and comments. Thanks are also in place to Michael Swendsen and his colleagues from Thrivent Financial, who provided invaluable data access, Jon Einar Flatnes for help on automating some intricate processes, and Dawn Johnson from CRF for insight of financial institutions' assessment of bankruptcy risk.

2. Previous Literature

2.1 Basic Theoretical Framework

2.1.1 Liquidity, Profitability and Wealth

The most popular theory for bankruptcy prediction is really a notional one. The theory is elaborated implicitly from financial measures in contrast to an economic concept being translated into a measure. This notional theory emanates from the perception of financial ratios as indicators of a firm's health. When the firm's indicators are "good" it is perceived as healthy, but it is perceived as unhealthy and at risk of bankruptcy if the indicators are poor.

Three major categories of these measurements egress: liquidity, profitability and wealth. A positive and high measurement of these three implies a lower risk of bankruptcy. The obvious weakness of this notional theory is its generality. On the flip side, however, this "weakness" ensures that the theory does not conflict with, and is inclusive of other more prescriptive theories.

2.1.2 Merton Model

The Merton theory models the equity as a call option on the assets where the strike price is the value of liabilities. In Merton's original formulation (Merton 1973), debt has an unambiguous maturity, and the option value is computed with this singular date. When the market value of the firm's assets falls below a certain level, the firm will default. On the upside, the equity owners keep the residual value, just like an equity option. Under the Merton model, the firm's future asset value has a probability distribution characterized by its expected value and standard deviation. The number of standard deviations the future value of assets is away from the default point is the 'distance to default'. The greater the value of the firm and the smaller its volatility, the lower the probability of default.

2.1.3 Gambler's Ruin

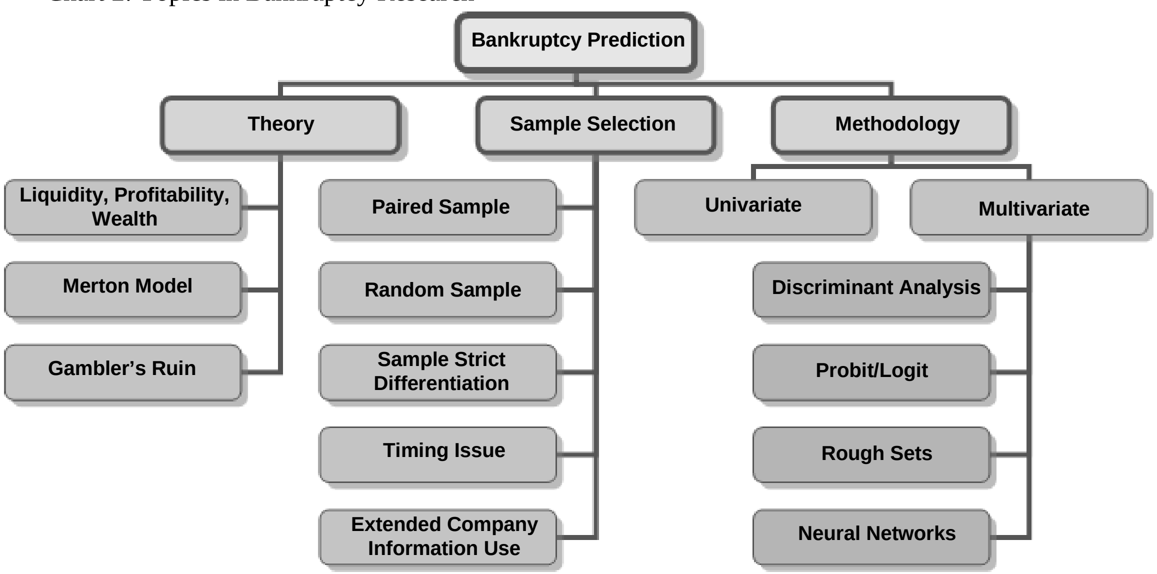
In another approach as developed by Wilcox (1971) the value of equity is a reserve, and cash flows either add to or drain from this reserve. In the case of a bankruptcy, the reserve is used up. The model comes from a well known statistical problem, and intuitively captures the default scenario for a firm. If one approaches a roulette wheel with X dollars and bets $1 with a 50% probability of receiving $2 or $0, what is the probability of losing all X dollars after N bets?

Wilcox set up a model where cash flow was with either positive or negative values, and the reserve is the value of book equity. One then computes the probability of default given the cash flows. The "distance to default" in this theory is the sum of book equity and expected cash flow divided by the cash flow volatility.

2.2 Empirical Research

In terms of analyzing the risks involved in lending, written records from Sumer circa 3000 B.C. (Falkenstein 2000) exist and accounting ratios have been examined since at least the 19th century (Dev 1974). The modern era of commercial default prediction, however, did not commence until the late 1960s. Three distinct areas of discussion can be discerned: theory, sample characteristics, and methodology (*Chart 2*).

Chart 2: Topics in Bankruptcy Research



The landmark paper was written by Beaver (1967) and all of the subsequent research stems from his findings. He found that several ratios differed significantly between failed and viable firms. Beaver recorded the differences of ratios between failed firms and viable firms and observed that as bankruptcy neared the ratios of the failed firm showed substantial deterioration, while the performance of the average nonfailed firm was relatively constant.

Beaver's model in essence, was that of the notional indicator theory but its framework was also quite similar to the Gambler's Ruin model. He viewed the firm as a reservoir of liquid assets, which are supplied by inflows and drained by outflows. Insolvency will set in if the reservoir is exhausted.

Several researchers have extended this approach, for example, adding drift in the cash flows to account for inflation. One extension of the Gambler's Ruin model (Scott 1981) relevant also to the Merton model is that a firm's book equity is not the total reserve. This adaptation recognizes the fact that companies do not go bankrupt because they run out of cash, but rather because people lose faith in them. If a firm's book equity is exhausted through losses and there remains market equity value, equity holders will have cause to infuse more book equity into the company to avert bankruptcy, which would otherwise eradicate their market value.

This phenomena is substantiated by the fact that the average market/book ratio is 3:1 (Falkenstein 2000), indicating that even if a firm lost all its book value, it still remains valuable. In addition, about 10% of all firms have negative net worth, yet the annual default rate on the entire population is around 1.5% per year. The use of market equity can better explain why technically insolvent companies avoid bankruptcy.

The implementation of the Merton model also makes some useful adjustments to its original formulation (Falkenstein 2000). The first adjustment addresses the trigger point of default, since the staggered debt maturities that companies actually have imply that the simple Merton formulation is ambiguous in practice. A firm can remain current on its debt even though technically insolvent (liabilities>assets). It can forestall and, with skill, avoid bankruptcy, even though the liability holders would like to liquidate.

In view of this complication, Crosbie (2002) uses half the value of long term debt plus current liabilities as a proxy for the 1-year default point, a formulation based on empirical analysis. Thus, in his formulation, the default point is not total liabilities as in the Merton model, but current liabilities plus half long term liabilities. This adjustment is consistent with the distribution of recovery rates on defaulted bonds. A final adjustment is made in mapping the distance from default into a probability (Crosbie 2002). In most cases, the probabilities calculated from the Merton model are much too low and are not consistent with reality (an average of around 1.5% default rates). Thus, Crosbie maps their initial output into actual defaults using historical data, as opposed to using the standard normal probability tables.

The adjustments suggest that the Merton model is more of a guideline than a rule for estimating a quantitative model. The final transformation from standard normal probabilities into empirical probabilities implies that even the strongest proponents of the approach do not take the Merton model literally.

The Merton and Gambler's Ruin models boil down to a univariate axiom: if either market equity goes to zero or if cash flow stays negative, the firm will fail. Under both models, prediction of bankruptcy is based primarily on a targeted ratio. For the Merton model this ratio uses primarily equity information, and for the Gambler's Ruin model, cash flow information is used. Only a small fringe of researchers use either the Merton or the Gambler's Ruin models because over-reliance on one targeted variable itself is sub-optimal. If the model is misspecified, a multivariate approach based not solely on the "distance to default" would be better (Falkenstein 2000).

This, however, has left bankruptcy prediction with very little guidance of what explanatory variables to use. In accordance with the notional theory Beaver (1967) tested the most popular ratios as used by lending practitioners. Altman (1967) for his Z-score model selected variables to include in a way that is the most popular even in today's research: by testing categories of ratios such as liquidity, profitability, etc., and then including the variables that have the highest explanatory power.

Perhaps the biggest problem for all of the bankruptcy studies has been the lack of a strong theoretical framework. Wilcox (1971) Blum (1974), Hol (2002) and others criticized the Z-score model for "searching" for the right variables to establish the model. They also argued that in the absence of a strong conceptual model scarce bankruptcy information was statistically "used up" by searching procedures. Wilcox and Blum in their papers explicitly postulated a general framework for variable selection based upon the Gambler's Ruin model. The common factors underlying the cash flow framework – liquidity, profitability, and variability – in essence didn't contradict Altman. Blum selected twelve variables to measure these cash flow parameters. Yet, contrary to his criticism of the Z-score, for future research he proposed that alternative ratios should be considered. In response Sinkey et al. (1981) explained that in order to determine which of the theoretically justified variables are the important ones, one needs to search. The debate until this date has latently stalled at this point with most researchers *searching* among theoretically appropriate variables.

The second topic of discussion addresses the effects of sample selection methods on predictive accuracy. Beaver's (1967) seminal research used a paired sample of nonfailed and failed firms by industry and asset size. The purpose of this technique was to control for factors that otherwise might mask the relationship between financial ratios and failure. He argued that these two factors should be controlled because across industries the same numerical value of a ratio may imply a different probability of failure and, given identical ratios, the smaller of two firms may have a higher probability of failure.

The shortcomings of a paired sample, as pointed out by Beaver himself, is that the controlled variables may be important predictors of failure yet remain undetected because their predictive power is masked by the paired sample technique. If a nonpaired sample is employed, the predictive power of all relevant variables can be determined. Altman (1977), for example, found that size was an important factor.

Ever since Taffler (1977), the trend has been shifting to using random samples with nonpaired firms. Zmijewski (1984) revisited the issue by focusing on the fact that researchers typically estimate financial distress prediction models on nonrandom samples as well as on the "complete data" sample selection criterion. Most estimation techniques assume the use of exogenous random sampling designs in which an observation is randomly drawn and the dependent and independent variables are observed. In contrast, researchers first observe the dependent variable and then select the sample. This approach violates the random sampling design assumption and causes both parameters and probability estimates to be asymptotically biased. Due to the higher distressed firm sample frequency, results will have lower distressed firm estimated error rates but higher nondistressed error rates. Zmijewski's results indicated that group error rates are associated with sample frequency rates and provide at least a partial explanation for the divergent distressed firm error rates reported in previous financial distress studies.

Another concern is raised by Ohlson (1980) regarding the fact that prior studies did not explicitly consider the timing issue – a company files for bankruptcy at some point in time after the fiscal year-end but prior to releasing financial statements. This leads to the assumption that some of these statements are available to predict bankruptcy when in reality they are not.

On a different note, Shumway (2001) argues that earlier research ignores data on healthy firms that eventually go bankrupt. By choosing when to observe each firm's characteristics arbitrarily, researchers introduce unnecessary selection bias into their estimates. Unlike previous research, Shumway argues that his approach can incorporate macroeconomic variables that are the same for all firms at a given point of time. Probably the most useful reason to use his approach is because by utilizing much more data a model may produce more efficient out-of-sample forecasts.

The third subject of discussion abundantly disputed in the literature concerns methodology. Especially in recent years, much attention is given to the choices of methodology. New methods like recursive partitioning, rough sets, neural networks, and genetic programming are commonly applied to the bankruptcy prediction problem.

While Beaver's (1967) initial approach was essentially univariate, Altman (1968) took Beaver's idea to a new level extending it to the multivariate case, which is used in all subsequent research. It seemed logical that as none of the financial measures were a perfect function of bankruptcy but had a high level of correlation, that together they could be of a better use than any of them alone. While clearly multivariate techniques are preferred today by most Econometricians, Falkenstein (2000) shows that univariate models quite often outperform the earlier multivariate models.

Default models are ideally suited towards binary choice modeling; the firm either fails or does not (1 or 0). Altman's (1968) approach using multiple discriminant analysis (MDA), *see Table 1*, has in general been replaced by probit and logit models. This seems logical because it avoids some MDA statistical requirements imposed on the predictors (Ohlson 1980)[2].

While several studies have found (Zavgren 1983) that in practice this violation is immaterial, a study by Lennox (1999) proves that probit and logit are indeed more efficient estimators than MDA as theoretically expected. Conditional logit reduces the estimation just to the following statement: given that a firm belongs to some prespecified population, what is the probability that the firm fails within some prespecified time period?

The choice between logit and probit is less important, as both give very similar results. Though MDA, logit, and probit generate roughly similar estimation results, there is a very different interpretation that arises from them (Ohlson 1980). MDA is about separating a sample into two groups: default and nondefault. Logit and probit are more useful to the interpretation of which observations have a higher probability of belonging in a certain group.

Altman, a proponent of MDA, states that the "presumption underlying credit scoring models is that there exists a metric than can divide good credits and bad credits into two distinct

[2] For example, it is required that the covariance matrix of the bankrupt and nonbankrupt firms is both normally distributed and equal. This assumption is obviously violated (ratio distributions are highly nonnormal, and failed firms have higher variability in their financial ratios as evidenced by Falkenstein 2000).

Note: Page 9 attached in separate file.

distributions" (Caouette et al. as from Falkenstein 2000). Alternatively, one can think of firms having a continuum of propensities to failure, where each has different probabilities of success associated with it.

MDA targets a bankrupt/nonbankrupt cutoff and the resulting accuracy, while the logit model produces a probability of bankruptcy that can be used for not only decision-making (loan/don't loan), but for estimating expected loss. This distinction can assist pricing decisions, as in RAROCK[3] models.

Overall the results of bankruptcy prediction have been auspiciously encouraging. Libby (1975) used a subset of Deakin's (1972) 14-variable set to determine whether quantitive models could outperform judgment from loan officers. He asked 16 loan officers from small banks and 27 loan officers from large banks to judge which 30 of 60 firms would go bankrupt within three years of the financial statements with which they were presented. The loan officers requested five financial ratios on which to base their judgments. While they were correct 74% of the time, this was inferior to such simple alternatives as the liabilities/assets ratio. The loan officers performed even worse when Casey (1980), refining Libby's approach, did not indicate the ratio of failure to nonfailure. This certainly speaks to the fact that models from the 70's already outperformed simple human ratio analysis.

Comparison between the results of various previous researchers is fruitless. According to Hol (2002) all of the studies use different time periods, industries and countries. In general it can be noted that more recent studies seem to be marginally more accurate mostly because of larger sample sizes and better information availability.

The general conclusion from previous research is that on the one hand each study by itself seems to provide a reasonable degree of differentiation between failed and non-failed companies, while on the other hand the various studies hardly show any agreement on what factors are important for failure prediction. More then 30 years of research have failed to produce agreement on which variables are good predictors and why. And in the absence of a thorough theory that provides testable hypotheses, each empirical result has to be evaluated on its own merits with a hope that patterns emerge from the multitude of results.

3. Conceptual model:

Concordant with previous empirical research, I construct a conceptual model to measure three key indicators of a company's health basing it on the popular notional theory of financial indicators, the Gambler's Ruin and Merton models.

$$\textit{Probability of bankruptcy} = f(\textit{liquidity}, \textit{profitability}, \textit{wealth})$$

This conceptual model finds a large support in the literature and most recent research follows this approach (Shumway 2001). Conceptually liquidity should indicate how a firm is able to meet its current liabilities. Profitability indicates whether the *reservoir* of resources is being drained or supplemented, and wealth indicates the current magnitude of the reservoir.

3.1.1 Ideal Data

Impeccably there would be a flawless measurement of the probability of bankruptcy. It would clearly and strongly mirror the true levels of a firm's probability of failure in any given point in time. It would be easily comparable for each firm. This measure would incorporate readily available financial information from the past and present that would have been measured consistently across industries and years. To arrive at this information uniform accounting principles would have been used and the measure would be easily interpretable.

3.1.2 Actual Data

For the purpose of this research, companies' bankruptcy was defined as a filing for Chapter 11 protection[4], which represents only a fraction of all bankruptcies. First, a list of all U.S. publicly traded companies with assets (as of November 2003) between 50 and 500 million dollars was generated, and then 850 randomly selected for my sample. Eighty four distressed companies with the same asset limitations (at time of bankruptcy) in 2001 and 2002 were selected. I also removed all financial companies from both groups because of their generally different financial structure (Altman 1968).

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[3] RAROCK – economic capital and risk-adjusted return on capital. It is industry's standard way of measuring risk-adjusted profitability (Marrison 2002).
[4] Companies that file for Chapter 11 protection will be referred to as distressed.

All of the financial data used in this research comes from *S&P's Compustat* with the names of the bankrupt companies extracted from *2003 Bankruptcy Yearbook and Almanac*. After retrieving 150 variables for each company to calculate ratios suggested by Falkenstein (2000) and Shumway (2001), and adjusting for missing data I was left with 418 non-distressed companies and 44 distressed ones. Similar to Shumway (2001), I requested thirteen years of information for each company prior to 2003 if they were non-distressed and thirteen years of information prior to bankruptcy for distressed companies. On average for each company in both groups, three years of information was available. Each distressed company contributed only one year of observations with financial information that was available a year before bankruptcy filing. The rest of the information for the distressed companies was added to the non-distressed category. After this I was left with 44 distressed and 1342 non-distressed observations. I further randomly subtracted 126 observations (about 10% of all firms) from the dataset as a hold-out sample and estimated my model on the 1260 observations left (about 90% of the sample).

Biases in using this information might exist. First of all, it might not have been accurately reported. This research assumes that all the information given is true, while in reality we know that falsification and misreporting occurs. Secondly, the financial data is not recorded using the same accounting principles, for example, some companies use LIFO versus FIFO, and differently value Goodwill. Thus some companies might have fundamentally different probabilities of bankruptcy and yet have similar accounting ratios. Thirdly, because *Compustat* has very limited categories for each financial statement, it could be combining categories for some firm financial statements differently than firms themselves that have fewer categories. Fourthly, some outlying values exist in the data set that could be hurting the model, however, no data points were eliminated because the sample is large and the consensus in the literature is to leave all values. Lastly, there seems to be more information for distressed companies, which would bias our estimates as well.

3.2 Actual Model

Without a strong theoretical framework that dictates the inputs of a model, there are two main methods used in the previous research (Falkenstein 2000). Forward selection method starts with the independent variables that have the highest univariate correlation and then adding lower correlation variables until they have no additional significance. Backward elimination method starts with all variables, then eliminates all the insignificant ones. Forward selection was used for this research because the immoderate amount of variables prevented backward selection.

After conducting the forward selection process the following model is specified:

Expected Signs: – + – – – +

$$P(bankruptcy) = \beta_0 + \beta_1 \cdot \frac{NI}{TA} + \beta_2 \cdot \frac{TD}{ME} + \beta_3 \cdot \frac{ME}{TA} + \beta_4 \cdot P\Delta + \beta_5 \cdot S\Delta + \beta_6 \cdot \frac{CL}{TA}$$

NI/TA – Net Income/Total Assets, *TD/ME* – Total Debt/Market Equity, *ME/TA* – Market Equity/Total Assets, *PΔ* – 6 month Stock Price change, *SΔ* – 3-year Sales Growth, *CL/TA* – Current Liabilities/Total Assets

Table 2: Expected Signs of the model (Dependent Variable: Probability of Bankruptcy)

Expected sign	Variable	Reasoning
–	NI/TA	Increase shows that the company is becoming more profitable, higher return on capital employed, and thus should have a larger reservoir to draw from as a cushion. This should result in a decrease in the probability of bankruptcy.
+	TD/ME	Shows the capital structure of the company and an increase implies higher leverage, thus higher probability of bankruptcy.
–	ME/TA	Also shows the capital structure of the company; an increase implies a rise in market perceived prospects for the company.
–	PΔ	Increase should indicate that investors have more confidence in a company’s future and its performance, with less fear of losing their investment (chance of bankruptcy).
–	SΔ	Sales growth represent the activity of the company and the potential to generate profits.
+	CL/TA	The rise of CL/TA indicates increasing liquidity problems as company can not meet its obligations and might need to file for bankruptcy protection.

The reasons why I use logit versus MDA are discussed above. The choice between logit and probit was purely accidental due to their similar performance.

4. Discussion of results

As can be seen from *Table 3* the signs on all of the independent variables are as expected. Furthermore, all of the independent variables are statistically significant at the 1% level except *3 year Sales growth*. The insignificance of sales growth might partially be attributed to the fact that it takes on a very long perspective, going back three years, when there might not have been any significant bankruptcy risk or the firm might have actually had an auspicious outlook.

In the summary of the marginal effects of each variable on the probability of bankruptcy (*Table 3*) we can see that the three variables that have the biggest effect on probability of bankruptcy are in order of importance: CL/TA, NI/TA and TE/TA. A one percent increase of

CL/TA increases the probability of bankruptcy by 0.02%. Since CL/TA partially proxies for the measurement of liquidity, the results are consistent with reality as the most common reason for bankruptcy is short-term liquidity problems (Falkenstein 2000). The next factor that affects probability of bankruptcy most is NI/TA, which makes sense given that higher profitability should unambiguously lead to less risk of bankruptcy. A percentage increase in TE/TA decreases probability of bankruptcy by 0.006%. Rest of the variables have smaller effects on bankruptcy.

Table 3: Summary of regression results
(Dependent Variable: Probability of Bankruptcy)

Variables	*Coefficients*	*Marginal Effects*[5]
Constant	-4.907437** (-9.195)	
Net Income/Total Assets	-2.109638** (-2.794)	-0.0076905
Total Debt/Total Equity	0.0006214** (2.617)	0.000000227
Total Equity/Total Assets	-1.733579** (-3.08)	-0.0063196
6 month stock price change	-0.016347** (-2.671)	-0.0000596
3 year Sales growth	-0.0049581 (-1.065)	-0.0000181
Current Liabilities/Total Assets	5.885188** (5.989)	0.0214538
Pseudo R^2	0.3948	y = 0.003658
χ^2	142.71**	
N	1260	

z-statistic in brackets, significance: * at the 5% level, ** at the 1% level

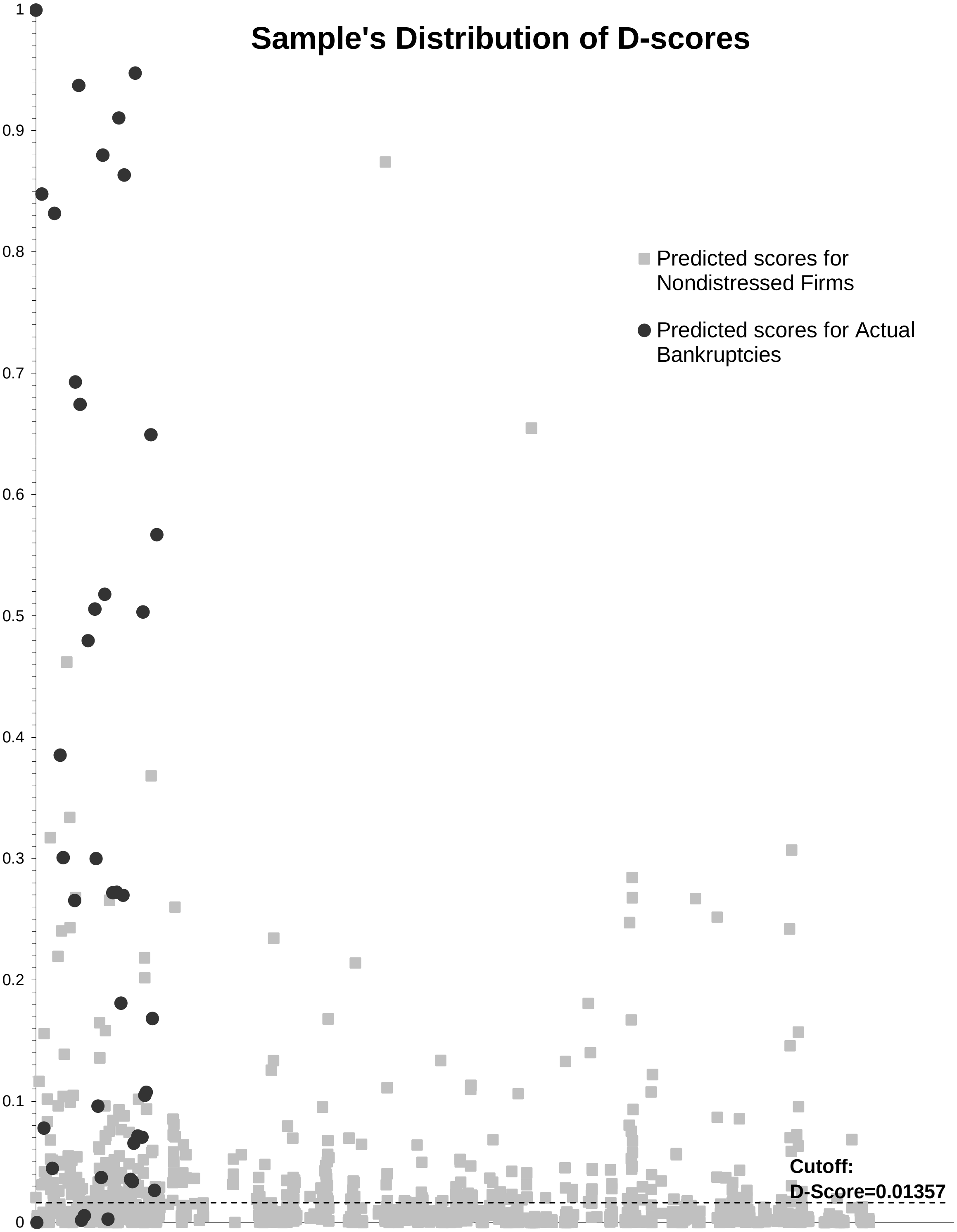
The model's most important characteristic, however, is its ability to predict the event of bankruptcy or its absence. In fact, the ratio of hits and misses (correct classifications and misclassifications) for distressed and non-distressed firms is inversely related. The more precise the predictions for distressed firms the more incorrect for the non-distressed. This can be seen in *Chart 3*. The predictive ability is really a measure of how good the model is, but within groups it is dependent on the cutoff point for D-Score. Type I errors are more costly than Type II errors, and therefore a truly minimized misclassification rate should incorporate these differing costs. The cutoff point is different for each individual practitioner depending on their idiosyncratic costs of misclassifying each group.

[5] Marginal Effects are measured as the percentage response in probability of bankruptcy given a 1% change in the independent variable.

$$Cutoff \,\Big|\, \min(c_D \cdot n_D + c_{ND} \cdot n_{ND})$$

c_D – cost of misclassifying a distressed firm, c_{ND} – cost of misclassifying a non-distressed firm, n_D – number of distressed firms misclassified, n_{ND} – number of non-distressed firms misclassified.

Chart 3



For this research the cost of misclassifying a distressed firm to misclassifying a non-distressed one was assumed an extreme \$100/\$1 as advised by Dawn Johnson, Asset and Portfolio Manager at CRF[6]. This produced the results shown in *Table 4*. The quick way of

Table 4: Summary of D-Score's classification results, firms

	Predicted	
Actual	Distressed	Non-distressed
Distressed	37	4
Non-distressed	351	868

Summary of D-Score's classification results, %

	Predicted	
Actual	Distressed	Non-distressed
Distressed	90%	10%
Non-distressed	29%	71%

assessing the performance of the model is to use a *naïve* rule of always predicting the group with the highest frequency[7]. If we follow the *naïve* approach we would lose \$4,100 versus \$800 if we use the D-Score model. Clearly this is a subjective measure as it depends on the costs of misclassification. However, even if the ratio is \$10/\$1, the loss for the *naïve* rule would be \$410 versus \$180 for D-Score. Ergo we see that, as the costs of misclassifying distressed firms increase relative to misclassifying non-distressed ones, it is more beneficial to use the D-Score.

What ultimately determines long-run acceptance and usage of a model is its out-of-sample performance. If it does not work in real life over a wide spectrum of companies its future is inauspicious at best. I left three randomly selected distressed firms and 123 non-distressed ones for the purposes of testing D-Score's performance on a hold-out sample. It is in place to acknowledge that this is a very small sample[8], and no precise assessment of the model should be made. At most it should be used as a subjective indication.

The results, illustrated in *Table 5*, show that 31 out of the 126 firms are correctly

Table 5: Summary of D-Score's classification results, firms

	Predicted	
Actual	Distressed	Non-distressed
Distressed	3	0
Non-distressed	71	52

[6] CRF – Community Reinvestment Fund

[7] In my sample bankruptcies are 3% of the population, this is twice as high as on average in reality according to Falkenstein (2000)

[8] I chose to use 90% of the available data for estimation of the model to produce more precise estimates, and thus only 10% of the data was left for out-of-sample testing.

Summary of D-Score's classification results, %

Actual	Predicted: Distressed	Predicted: Non-distressed
Distressed	100%	0%
Non-distressed	57%	43%

classified. The precision for the hold-out-sample for the distressed firms is in fact better than that of the in-sample. Nevertheless, statistically it should not be expected that this is going to be true for other out-of-sample firms. At best what this shows is that D-Score cannot be discarded immediately and further testing on more firms is in place.

The average percentage of correct classifications for distressed firms in the previous research is about 90% for in-sample firms, with out-of-sample accuracy well below that. Ninety percent is not a magical number, but it is a useful point of reference, when thinking about the D-Score, to note that it is not 20% or 99%. We also have to keep in mind that the sample size varies among studies considerably, which will bias the accuracy up or down depending on the particular sample size and characteristics. On a superficial level, D-Score, while less accurate as compared to the latest studies, displays similar precision.

In addition D-Score offers an advantage comparatively to some other models as it requires very little information to be calculated (*Table 6*). Only 10 inputs are required to compute the score, which is less than, for example, the industry's standard RiskCalc^{TM}'s 17 from Moody's. D-Score's parsimony might be preferred, because in the presence of high correlation among variables, the variances of coefficients are inflated. The added information from extra variables might be outweighed by imprecision in the coefficient estimates.

Table 6: D-Score's Inputs

Inputs (10)	Ratios (6)
Current Liabilities	3 year Sales growth
Net Income	6 month stock price change
Sales (4 years)	Current Liabilities/Total Assets
Stock price (6 months prior and at the time of evaluation)	Net Income/Total Assets
Total Assets	Total Debt/Total Equity
Total Equity	Total Equity/Total Assets

A final way of viewing the results is to develop what Altman (1968) calls a "zone of ignorance", a sort of gray area that is susceptible to misclassification. In other words, if the company scores in the general vicinity of the cutoff point, one should further research the company at hand. As mentioned at the outset of this paper, D-Score is an *objective check* to assess one’s probability of bankruptcy and should be used in addition to other methods that might capture, for example, qualitative information that D-Score overlooks.

5. Conclusion

The prediction of the phenomena of bankruptcy can be greatly utilized in such diverse areas as credit risk assessment, internal performance assessment and particular portfolio position decisions. This paper seeks to improve upon the previous research of bankruptcy prediction by developing a model using forward selection process in a relaxed Gambler’s Ruin and Merton model context. It takes advantage of the most recent financial data for middle market publicly traded firms and uses multi-year observations per firm.

D-Score can be used as an *objective check* in addition to other tools to asses the probability of bankruptcy. D-Score’s in-sample and out-of-sample performance is encouraging as compared to other recent models. For more robust evaluation of the model’s performance, it needs to be tested on a larger sample of companies not used in the estimation.

A potential area of theoretical research lies in the further conceptualization of a strong theoretical framework. This would ease the task of model specifications and could potentially bring some standardization in the research. An area of practical improvement is to introduce differentiation among industries and different time periods. This could possibly assist in the explanation of whether the relationship between ratios and probability of bankruptcies change over time and whether this is the reason why there is no consensus on prescribed variables in bankruptcy prediction models.

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Statistics for in-sample data:

	yhat	D	ND
Average	0.03254	0.365853	0.021328975
Max	0.999292	0.999292	0.874019
Min	1.07E-21	1.21E-05	1.07E-21
S.D.	0.099582	0.33417	0.052130113

	td_te	sgrowth3	price6m	cl_ta	ni_ta	me_ta
Average	124.395	22.92966	3.408009	0.272921	-0.115	1.869288
Max	6369.6	971.93	1370.59	7.859869	1.127697	48.15133
Min	0	-88.05	-99.42	0	-19.3396	0.000731
S.D.	370.318	58.98629	69.26214	0.340081	0.635358	3.620107

Table 1: Summary of Literature

Major research on the subject

Study	Independent Variables	Data Type *D*	Data Type *ND*	Data Type	Estimation Technique	Results
Altman (1968)	WC/TA, RE/TA, EBIT/TA, MVE/TD, S/TA	33	33	Industrial corporations that filed for Chapter X between '46-'65	MDA	Ratio movements prior to bankruptcy corroborated the model's findings that bankruptcy can be accurately predicted up to two years prior to actual failure.
Ohlson (1980)	WC/TA, SIZE, TL/TA, CL/CA, OENEG, NI/TA, FU/TL, INTWO, CHIN	105	2,058	Publicly traded industrial companies from 1970 to 1976, Source: Compustat	Logit	1. Predictive power depends on when the information is assumed to be available 2. Predictive improvement requires additional predictors
Zmijewski (1984)	NI/TA, TL/TA, CA/CL, Ln(firm age)	96	3,880	Publicly traded industrial companies, 1975-1980	Probit	Firm age is an important factor. Parsimonious models have even better out of sample performance than too elaborate ones.
Falkenstein (2000)	Assets/CPI, I/COGS, TL/TA, Income Growth, NI/TA, Quick ratio, RE/TA, SalesΔ, Cash/TA, DSCR	1,975	24,710	Moody's Default Data Base, 1990 to 1999	Probit	RiskCalc™ is superior to other similar benchmark models. The increased accuracy as compared to other models is in part attributed to the large sample size as well as meticulous data transformation and normalization.
Shumway (2001)	NI/TA, TL/TA, Relative size, Stock return, Sigma	118	1,704	Industrial corporations over 31 years	Logit	His model works better than Zmijewski's or Altman's models. Utilizing multi-year information for each company is preferable. Half of previously used variables appear to be insignifficant.

Note: D – distressed, ND – non distressed, CA/CL – Current Assets/Current Liabilities, CHIN – Net income change between two reporting periods, CL/CA – Current Liabilities/ Current Assets, DSCR – Debt Service Coverage Ratio, EBIT/TA - EBIT/Total Assets, FU/TL – Funds provided by operations divided by total liabilities, I/COGS – Inventories/Cost of Goods Sold, INTWO – One if net income was negative for the last two years or 0 otherwise, MVE/TD - Market Value Equity/ Total Debt, NI/TA – Net Income/ Total Assets, OENEG – One if total liabilities exceed total assets, zero otherwise, RE/TA – Retained Earning/Total Assets, RE/TA - Retained Earnings/Total Assets, Sigma – volatility measure, SIZE – log(Total Assets/Consumer Price Index), TL/TA – Total Liabilities/ Total Assets, WC/TA – working capital to total assets, WC/TA - Working Capital/ Total Assets