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Assessing the Probability of Bankruptcy

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Abstract:

Knowing whether or not a company is financial stable has always been a top concern for analysts and money managers. This paper compares the effectiveness of default prediction using two different types of measures: accounting and market based. Accounting measures have been the most popular even though, according to theory, a market based measure reflects all available information. Theory goes as far to say that accounting measures can add no incremental value to a market based measure. In my research I found that accounting based measures can be effective in their predictive power; the market-based measure (BSM) results were much more difficult to estimate within the limits of this research project.

I. Introduction

My paper is closely related to Hillegeist, Cram, Keating, and Lundstedt (2002). In their paper, they compare two common aggregates of information: accounting-based and market-based measures. The popular accounting-based measures of Altman (1968) and Ohlson (1980), known as Z-Score and O-Score, are derived from public information and should be accurate indicators of how well a company is doing. The market-based measure is one taken from the work of both Black and Scholes (1973) and Merton (1974), henceforth BSM. Any market-based measure should reflect all information available at a given time and beliefs regarding the future. With an understanding of both of these measures, the BSM measure could be more informative then the Z-score or O-score, especially if the past is expected to be drastically different than the future.

My approach is to replicate the process of Hillegeist et al. (2002) in calculating the fore mentioned information aggregates extending their analysis seventeen years through 2014. The bankruptcy sample I use is smaller, 183 bankruptcies compared to their 516 bankruptcies. Hillegeist et al. (2002) uses a discrete hazard model to incorporate multi-period changes. I use a single period logit model for my analysis due to the complexity of the discrete hazard model. I was able to come to similar conclusions surrounding the effectiveness of accounting-based measures and their predictive power; the market-based measure (BSM) results were much more difficult to estimate within the limits of this research project.

II. Research Design

a. Accounting-based

The Z-Score and O-Score equations come from the work of Altman (1968) and Ohlson (1980) respectively. Altman (1968) has become the most influential in corporate bankruptcy prediction. He developed the Z-Score through choosing the five variables that had the most predictive power in a multivariate discriminant analysis model, MDA. In order to estimate the Z-Score coefficients, I required working capital over total assets (WC/TA), retained earnings over total assets (RE/TA), earnings before interest and taxes over total assets (EBIT/TA), market value of equity over total liabilities (VE/TA) and sales over total assets (S/TA). A company that has a Z-Score above 2.675 is not likely to go bankrupt, while a company with a Z-Score below 2.675 has a higher probability of bankruptcy. Altman's (1968) original Z-Score is the following equation:

$$Z - Score = 0.12\,\frac{WC}{TA} + 0.014\,\frac{RE}{TA} + 0.033\,\frac{EBIT}{TA} + 0.006\,\frac{VE}{TA} + .999\,\frac{S}{TA}$$

Ohlson (1980) use multinomial choice techniques such as maximum-likelihood logit and probit. Hillegeist et al. (2002) argues that these methods are preferable to MDA. In my research I found why logit regression is preferred for two groups: it has fewer assumptions, similarity to regression, and has straightforward statistical tests. However, there must be a large sample for the increased accuracy of results. The O-Score uses nine variables and a constant to determine bankruptcy likelihood. For the O-Score, I needed ln(total assets) (SIZE), total liabilities over total assets (TL/TA), working capital over total assets (WC/TA), current liabilities over current assets (CL/CA), net income over total assets(NI/TA), funds from operations over total liabilities

(EBITDA/TL), an indicator for if net income had been negative for two consecutive years (NITWO), an indicator for if owners' equity is negative (OENEG) and a change in net income from year to year (CHNI). If a company has a score greater than 0.5, it has a higher probability of default. The following is Ohlson's (1980) original O-Score equation:

$$O - Score = -1.32 - 0.407\, SIZE + 6.030\, \frac{TL}{TA} - 1.430\, \frac{WC}{TA} + 0.076\, \frac{CL}{CA} - 2.370\, \frac{NI}{TA}$$
$$- 1.830\, \frac{FFO}{TL} + 0.285\, NITWO - 1.720\, OENEG - 0.521\, CHNI$$

A single period logit model was used as my regression technique for the estimation of both the Z-Score and the O-Score. In Hillegeist et al. (2002) they diverge from this technique to try solving some of the problems that may arise. Including sample selection bias that arises from using only one, non-randomly selected observation per firm and failure to model time-varying changes in the underlying or baseline risk of bankruptcy. They chose to use a discrete hazard model to be able to account for this underlying risk of going bankrupt in a given period to correct this sample selection bias. Although these are valid concerns, the discrete hazard model was outside the limits of my research project. I chose to use the logit model due to its simplicity and proven effectiveness.

b. Market-based

Based on BSM theory, one can understand equity to be valued the same as a call option on the market value of a given firm's assets. The following formula is for a BSM European call option:

$$V_E = V_A N(d1) - Xe^{rt} N(d2)$$

In this formula, V_E is the value of equity; V_A is the value of assets; X is the face value of debt maturing in t periods; r is the risk-free rate; and N(d1) and N(d2) are the standard cumulative normal of d1 and d2:

$$d1 = \frac{\ln\left[\frac{V_A}{X}\right] + \left(r + \frac{\sigma^2{}_A}{2}\right)t}{\sigma_A\sqrt{t}}$$

$$d2 = \frac{\ln\left[\frac{V_A}{X}\right] + \left(r - \frac{\sigma^2{}_A}{2}\right)t}{\sigma_A\sqrt{t}}$$

N(d2) is the risk-neutral probability that the European call option will expire in the money, and N(-d2) is the risk-neutral probability of bankruptcy. Thus, N(-d2) is the probability of bankruptcy or BSM-PB

In Hillegeist et al. (2002), they attempt to adjust for the fact that risky assets will earn a risk premium. They proxy for μ by using an equation for adjusted return on the book value of assets:

$$\mu = \frac{NI_{t-1} + IntExp_{t-1} * (1 - TR)}{TA_{t-1}}$$

These lagged variables are net income, interest expense and total assets. I assumed TR (tax rate) of 35%.

They also assume a continuous payout rate of dividends, D for convenience, instead of a quarterly dividend. They define D in terms of total assets.

These terms of μ and D are used to see if there is more explanatory power through using them in place of r and dividends=0. The four different scenario combinations are: (r, 0), (μ, 0), (r, D) and (μ, D). I used all four of these combinations to test for their effectiveness. The equation for predicting the probability of bankruptcy, while substituting in μ for r and D for 0, or BSM-PB (μ, D) is as follows:

$$BSM - PB(D, \mu) = N\left(- \frac{\ln\left[\frac{V_A}{X}\right] + \left(\mu - D - \frac{\sigma^2{}_A}{2}\right)t}{\sigma_A\sqrt{t}} \right)$$

III. Data

My main datasets include both CRSP and Compustat. CRSP most importantly provided me with the delisting indicators and Compustat supplied me with the fundamentals annual that I needed to create the ratios to determine the Z-Score, O-Score and some of the inputs for the BSM variable. I also reference the Federal Reserve Economic Data website for the yearly risk-free rates from 1979-2014.

My main objective with my data was to have the best sample possible within the limits of my project. Like Hillegeist et al. (2002), I started my sample in 1979 the year directly proceeding the Bankruptcy Reform Act of 1978. I included all firm observations through December of 2014. Hillegeist et al. (2002) found their bankruptcy filings from Moody's Default Risk Services' Corporate Default database and SDC Platinum's Corporate Restructurings database. Using these databases, they had a total of 516 bankruptcies. I use CRSP to provide me with the delisting indicators for the event of default. This provided me with 183 companies that were delisted due to bankruptcy from 1979 through 2014. Although the number of bankruptcies I had to work with was substantially less than Hillegeist et al. (2002), I did have more than both Altman (1968) with 33 bankruptcies and Ohlson (1980) with 105 bankruptcies.

The BSM required: lagged net income (NI_{t-1}), lagged interest expense ($IntExp_{t-1}$), lagged total assets (TA_{t-1}), book value of total assets (V_A), book value of total liabilities (X), and standard deviation of the book value of total assets (σ_A).

After pulling and merging both datasets and checking for missing data points, I was left with a total of 234,323 firm year observations and 183 firm bankruptcies.

IV. Results

Table 1 is a summary of all the variables used in the calculation of the Z-Scores and O-Scores. It includes all of the sample statistics: number of observations, mean, standard deviation, as well as minimum and maximum values. The results have been winsorized. The NITA negative mean seemed interesting to me.

Table 2 includes bankruptcy rates for each year from 1979-2014. It shows the number of firms for each year used in the analysis, number of bankruptcies per year and the total percentage of firms that went bankrupt. There is an increase in bankruptcies in the early 1990's and the early 2000's. These were possibly due to Black Monday and the Tech Bubble.

Table 3 shows the breakdown of the Z-Score and O-Score regression estimators. There is a column for both Altman's and Ohlson's original findings along with my estimations for each. Each coefficients estimate is given along with their significance level. There was substantial significance in the Z-Score model with all five of the variables all at the 1% level The O-Score was significant for many coefficients as well: the intercept, size, total assets over total liabilities, the indicator for if net income had been negative for two consecutive years, and the indicator for if owners' equity is negative, all at the 1% level. The funds from operations over total liabilities was also significant at the 5% level. It seems that both models have powerful explanatory strength.

Table 4 shows the sample statistics for each of the Z-Scores both original and new, the O-Scores both original and new, and the BSM results. Those results that are statistically significant are labeled as such. It was interesting to me that both estimations of the Z-Score and O-Score were statistically significant at the 1% or lower.

V. Conclusion

The coefficient estimates I found for the Z-Score similar in their accuracy in predicting the probability of bankruptcy compared with those of Altman (1968). This was a great finding especially due to my use of a larger sample size and the logit technique versus the MDA model approach.

I also found that my estimates of the O-Score were similar in their predictive power when compared with those of Ohlson (1980). Although our results differed, their predictive power on the dataset were both very effective. This was probably due to our using the same logit technique and a similar sample size of bankruptcies.

Due to some of the complexities of the BSM, I was unable to accurately estimate some of the key inputs needed by the formula. I used the book value of assets to substitute for the market value of assets. Upon further reading I found that Hillegeist et al. (2002) had to estimate the market value of assets (V_A) and standard deviation of the market value of assets (σ_A) using an optional hedge formula. I believe that these simulations are the reasons why I was unable to get results for my BSM measures. These calculations were not within the limits of my research project. Given this process I believe the BSM results would have been accurate and display predictive power.

To conclude, I found that using accounting based predictive models is very effective and statistically significant. The theory that a BSM contains all information still holds. However, there are other more complex techniques that provide us with these results. The methods in Hillegeist et al. (2002) were outside the limits of this project. I see many additional ways to continue in extending my research: applying a discrete hazard model, continuing with Hillegeist et al. (2002) in calculating more accurate inputs to the BSM, or using real observable changes in option prices.

References:

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Table 1

Sample Statistics for Z-Score and O-Score Inputs

Variable	Obs.	Mean	St. Dev.	Min.	Max.
WCTA	170,359	0.25365	0.27199	-0.6144	0.87653
RETA	208,181	0.44782	0.28292	-0.4806	0.96837
EBITTA	199,566	0.00017	0.24274	-1.3213	0.35907
TLTA	207,627	0.54599	0.28184	0.03117	1.47401
CLCA	170,306	0.67852	0.69664	0.04303	5.05899
NITA	207,606	-0.04568	0.27022	-1.6071	0.29539
FFOTL	201,939	0.04903	1.01201	-5.9114	2.57833
STA	207,067	0.96464	0.84148	0	4.23125
VETL	202,914	5686.18	13843.1	0	99829.7
CHNI	186,784	0.00518	0.54558	-1	1
SIZE	208,210	5.29063	2.40646	0.32710	11.33
NITWO	234,506	0.14115	0.34817	0	1
OENEG	234,506	0.14160	0.34864	0	1

Table 2

Bankruptcy Rate per Fiscal Year

Fiscal Year	Number of Firms	Number of Bankruptcies	Percentage of Failed Firms
1979	**4751**	**1**	0.023%
1980	**4906**	**3**	0.069%
1981	**5203**	**3**	0.065%
1982	**5572**	**5**	0.103%
1983	**6024**	**5**	0.095%
1984	**6206**	**6**	0.109%
1985	**6425**	**2**	0.036%
1986	**6829**	**6**	0.101%
1987	**7145**	**1**	0.016%
1988	**7213**	**8**	0.126%
1989	**7215**	**2**	0.032%
1990	**7437**	**7**	0.112%
1991	**7817**	**14**	0.220%
1992	**8377**	**21**	0.311%
1993	**9178**	**11**	0.147%
1994	**9550**	**0**	0.000%
1995	**9993**	**4**	0.049%
1996	**10206**	**1**	0.012%

Fiscal Year	Number of Firms	Number of Bankruptcies	Percentage of Failed Firms
1997	**9995**	**3**	0.035%
1998	**9785**	**3**	0.036%
1999	**9436**	**4**	0.049%
2000	**8986**	**7**	0.089%
2001	**8404**	**8**	0.110%
2002	**8162**	**16**	0.231%
2003	**8011**	**5**	0.075%
2004	**7916**	**7**	0.105%
2005	**7922**	**4**	0.060%
2006	**7888**	**1**	0.015%
2007	**7830**	**1**	0.015%
2008	**7604**	**4**	0.060%
2009	**7338**	**8**	0.124%
2010	**7173**	**3**	0.046%
2011	**7073**	**3**	0.046%
2012	**6596**	**2**	0.033%
2013	**6209**	**2**	0.035%
2014	**5815**	**2**	0.041%

Table 3

Z-Score and O-Score estimations

Altman's (1968) Model	Altman's Original Estimates	Revised Parameter Estimates	**Ohlson's (1980) Model**	Ohlson's Original Estimates	Revised Parameter Estimates
Intercept		-2.7463*	Intercept	-1.320	-11.1874*
WC/TA	-0.12	1.2786*	Size	-0.407*	0.1566*
RE/TA	-0.14	-2.7656*	TL/TA	6.030*	3.4169*
EBIT/TA	-0.033	-2.4518*	WC/TA	-1.430**	0.5754
VE/TL	-0.006	-0.0411*	CL/CA	0.076	0.00745
S/TA	-0.999	0.2935*	NI/TA	2.370**	0.1033
			FFO/TL	-1.830*	-0.2713**
			NITWO	0.285	1.1264*
			OENEG	-1.720*	1.0583*
			CHIN	-0.521*	0.0484
-2 Log		2398.422	-2 Log		2,320.892
Observations		163,707	Observations		151,962

* significant at 1% or lower
** significant at 5% or lower
*** significant at 10% or lower

Table 4

Sample Statistics and Predictive Power

Variable	Obs.	Mean	St. Dev.	Min.	Max.
ZSCORE*	163,707	39.77892	84.8051	-0.03677	603.3342
ZSCORENEW*	163,707	266.5619	582.385	-5.00611	4,108.66
OSCORE*	152,108	-0.622625	3.29882	-11.0763	21.7583
OSCORENEW*	152,108	-8.275825	1.18581	-11.7123	-2.42279
$BSMPB1_1$	207,031	0.003636	1.00108	-3.98516	4.62651

* significant at 1% or lower
** significant at 5% or lower

1. I am only reporting one BSM-PB. I ran 4 different BSM-PB as was discussed in "Research and Design" earlier in the paper, namely (rfrate, 0), (μ, 0), (rfrate, D), and (μ, D). They all returned the same result. I ran correlation tests on BSM-PB 1-4 and found them perfectly correlated. D was not significantly different than zero. Although μ and the risk free rate were significantly different, when applied to the probability of bankruptcy equation and passed through the normal distribution, they were perfectly correlated.