Z SCORES—A GUIDE TO FAILURE PREDICTION

By Gregory J. Eidleman

Problems of business failures are still assuming an increasing importance. In a typical week, over 300 companies will fail—rates higher than at any time since the 1930s. The combination of intensively competitive markets and increasing debt burdens is likely to produce even greater numbers of failures whenever a downturn in the economy occurs.

Financial-statement analysis looks at a firm's past performance to predict its future condition. Some users of ratio information have very specific concerns:

- ***Lenders*** are interested in the firm's ability to meet the payments over the life of the loan.
- ***Auditors*** are interested in judging whether financially troubled companies are likely to continue as a going concern.
- ***Managements*** are interested in knowing the problems they are about to face and, where appropriate, taking corrective action.

Methods for Statistical Approaches to Ratios

Statistical ratio models are usually created by academics. They often are developed with the following pattern:

- ***Identify a sample of failing firms.*** These would meet some predetermined criterion of failure such as bankruptcy, loan defaults, etc. A sample of around 30 is probably needed for results to have statistical validity.
- ***Find a group of comparable firms.*** These would be similar with respect to size, industry, etc. The only difference is these businesses are in a healthy state.
- ***Analyze differences between healthy and failing businesses.*** Computer analysis should reveal which ratios are consistently and significantly different between the two groups.
- ***Derive a scoring system containing the significant ratios.*** This usually takes the form of a score such that score = [ratio #1 * weight attached to ratio #1] +[ratio #2 * weight attached to ratio #2] ... etc.

The formula would tell us whether any given firm has a profile that more closely corresponds to other successful or failing businesses.

- ***Evaluate new firms.*** This involves scoring their financial ratio profile against our database. Eventually you can track the performance of the model's assessment with what actually happened, e.g., did the firm go bankrupt in the real world?

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Altman's Z Score

Altman's model is probably the classic of this genre. The original data sample consisted of 66 firms, half of which had filed for bankruptcy under Chapter 7. All businesses in the database were manufacturers, and small firms with assets of less than $1 million were eliminated. The original Z score was as follows:

$$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$$

Where X_1 = Working Capital/Total Assets. This measures liquid assets in relation to the firm's size. Altman, interestingly, mentions that the most widely used current and acid ratios were not as good predictors as this measure.

Where X_2 = Retained Earnings/ Total Assets. This is a measure of cumulative profitability that reflects the firm's age as well as earning power. Many studies have shown failure rates to be closely related to the age of the business.

Where X_3 = Earnings Before Income Taxes/Total Assets. This is a measure of operating efficiency separated from any leverage effects. It recognizes operating earnings as a key to long-run viability.

Where X_4 = Market Value of Equity/ Book Value of Debt. This ratio adds a market dimension. Academic studies of stock markets suggest that security price changes may foreshadow upcoming problems.

Where X_5 = Sales/Total Assets. This is a standard turnover measure. Unfortunately, it varies greatly from one industry to another.

Altman found the following significantly different ratio profiles for the two groups:

	Bankrupt	Nonbankrupt
X_1	-6.1 %	41.4 %
X_2	-62.6 %	35.5 %
X_3	-31.8 %	15.4 %
X_4	40.1 %	247.7 %
X_5	1.5 %	1.9 %

The resulting Z values are as follows:

	X_1	X_2	X_3	X_4	X_5	Z
Zbr=	-.07	-.87	-1.04	+0.24	+1.49	= -0.25
Znbr=	+.49	+.49	+.50	+1.48	+1.89	= +4.88

To assess any firm's likelihood of bankruptcy, we would compare their Z score with the predetermined cutoffs shown below.

Bankrupt	<1.81
Zone of ignorance	1.81-2.99
Nonbankrupt	>2.99

The Z score has proven successful in the real world. It correctly predicted 72% of bankruptcies two years prior to the event. Z score profiles for failing businesses often indicate a consistent downward trend as they approach bankruptcy.

Some Cautions

Altman's Z score is the tried and tested formula for bankruptcy prediction. It has been demonstrated to be quite reliable in a variety of contexts and countries. It is not designed to be used in every situation. Before using a Z score to make predictions, one must ensure the firm being examined is comparable to the database. The two major issues are discussed below.

Privately Held Firms. If a firm's stock is not publicly traded, the X4 term (Market Value of Equity/Book Value of Debt) cannot be calculated. To correct for this problem, the Z score can be reestimated using book values of equity. This provides the following score:

$$Z_1 = .717X_1 + .847X_2 + 3.107X_3 + .420X_4 + .998X_5$$

The predetermined cutoffs for the Z_1 score are as follows:

Bankrupt	<1.23
Zone of ignorance	1.23-2.90
Nonbankrupt	>2.90

Nonmanufacturing Firms. The X_5 (Sales/Total Assets) ratio is believed to vary significantly by industry. It is likely to be higher for merchandising and service firms than for manufacturers, since the former are typically less capital intensive. Consequently, nonmanufacturers would have significantly higher asset turnover and Z scores. The model is thus likely to underpredict certain sorts of bankruptcy. To correct for this potential defect, Altman recommends the following correction that eliminates the X_5 ratio:

$$Z_{11} = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$$

The predetermined cutoffs for the Z score are as follows:

Bankrupt	<1.1
Zone of ignorance	1.1-2.6
Nonbankrupt	>2.6

Small Firms. Altman's original data sample consisted of large firms with assets in excess of $1 million. The most recent model had businesses with assets averaging approximately $100 million. If it is believed that smaller firms have significantly different ratios from larger entities, then the use of Z scores may not be appropriate.

An Example of Misclassifications

The following shows how using an inappropriate Z score might cause an improper classification to occur. JIMMY, INC., is a service dealership for heavy equipment. The conventional Z score of 1.73 indicates a firm in the zone of ignorance. This is largely because of the asset turnover (X5) ratio. When the modified Z score of -.96 is employed, this distortion is removed and the firm clearly falls into the bankrupt classification.

Conventional Z Score.

$Z = 1.2X_1 + 1.4X_2 + 3.3X_3 + 0.6X_4 + 1.0X_5$

WORK CAP/TOTAL ASSETS X_1	-0.08299
RET EARN/TOTAL ASSETS X_2	-0.15825
IBT/TOTAL ASSETS X_3	0.072175
MKT VAL EQTY/B VAL DEBT X_4	0
SALES/TOTAL ASSETS X_5	1.903069
Z SCORE	1.733989
High Limit	2.99
Low Limit	1.81

Z Score for Nonpublicly Traded Nonmanufacturing.

$Z_{11} = 6.56X_1 + 3.26X_2 + 6.72X_3 + 1.05X_4$

WORK CAP/TOTAL ASSETS X_1	-0.45373
RET EARN/TOTAL ASSETS X_2	-0.36851
EBIT/TOTAL ASSETS X_3	0.146976
MKT VAL EQTY/B VAL DEBT X_4	-0.28485
Z SCORE	-0.96012
High Limit	1.1
Low Limit	2.6

How Useful Are Statistical Models?

A decade ago, the use of Z Scores was virtually unheard of among practicing accountants. Today they are used by auditors, management consultants, and courts of law, and as part of many database systems used for loan evaluation. Those who advocate the use of these approaches argue as follows:

- They are more precise and lead to clearer conclusions than a mass of contradictory ratios. They measure the extent of our uncertainty.
- They are uniform and leave less room for the quirks and inaccuracies of judgment that some individuals possess.
- Their reliability can be evaluated statistically. They are based on past experience rather than merely on someone's unverified opinion.
- They are faster and less costly to work with than traditional tools.
- They can weed out the two extremes of the spectrum in an economical fashion. This allows the analyst to focus on the gray area where experience and judgment are needed to compensate for what the computer misses.

Based on experience with financial models, users must be fully aware of the pitfalls involved. Some of these are as follows:

- Many scoring systems can behave strangely; when ratios take on abnormal values they often produce erroneous results. It is dangerous to assume that sophisticated tools can be used by the untrained. They can be blinded by their apparent accuracy and sophistication. Models move us one stage further from the raw accounting data. Only experienced users realize how imprecise "exact" information sometimes is.
- Models often do not give a clear result. Whenever there is doubt, we must look to the intangibles and address the qualitative issues.
- Most users lack an adequate database to construct their own models. As a result, they must purchase a custom-built one (expensive) or rely on models like those described here that may not meet their specifications exactly.

For better or worse, the era of computer assisted statement analysis is with us. In the future it is likely to spread more widely. Whether Z scores and the rest can outperform traditional approaches is a question we can only answer in the real world. In my opinion they are a valuable, cost-effective weapon to be added to the arsenal. Provided they are used to complement our existing knowledge and we are not fooled by their apparent exactness, they can only improve the quality of our work. ❑

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