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New risk analysis tools with accounting changes: adjusted Z-score

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Altman's Z-score has been used for several decades to calculate bankruptcy probability. However, the conventional Z-score fails to consider possible earnings manipulations that could change the fundamental accounting figures and their implications for investors' decision models. We reconstruct the Z-score, making adjustments for earnings management. We apply the adjusted Z-score to measure the degree of deviation from bankruptcy probability for the bankruptcy sample. We find that the Z-score is overstated (respectively, understated) for the income-increasing (respectively, income-decreasing) earnings-management sample. Furthermore, we find that the adjusted Z-score performs better than the Z-score for bankruptcy predictions.

1 INTRODUCTION

In the financial market, to rate credit risk, analysts or investors rely on financial statements. For example, most ratio analyses or credit analyses use components of financial reporting along with other firm-specific daily news on firm-specific operations in order to measure its business risk. Predicting bankruptcy using Altman's Z-score has been one of the more widely used of these methods for several decades (Altman (1968)). Since its proposal in the 1960s, the Z-score formulas have been modified for application in different industries and are widely accepted by auditors, courts and in the loan evaluation process. Furthermore, along with other bankruptcy predicting models, the Z-score is often used as a proxy for business risk in other studies (Allen *et al* (2006); Landsman *et al* (2009); and Menon (2010)) due to its ease of application.

One of the main characteristics of the Z-score is the use of financial reporting. Specifically, the Z-score is calculated based on major accounting figures (ie, working capital, earnings and retained earnings) along with stock market information. Thus, accounting attributes play a major role in the Z-score formula, and any change in accounting attributes is significant for the accuracy and the predictability of the Z-score. The Z-score therefore has an inherent structure that is sensitive to changes in accounting figures. While the industry-wide application of the Z-score has rarely changed from using a particular combination of parameters, the financial-reporting environment has changed drastically (Hoffman and Patton (2002)). More distinctively, the recent globalization of accounting standards has changed the accounting paradigm from a rule-based to a principle-based set of standards aiming for harmonization with the International Financial Reporting Standards (IFRSs) (Benston *et al* (2006); Jamal *et al* (2010); and Jamal and Tan (2010)).

As mentioned above, the Z-score is derived from accounting figures reported in financial statements that represent different business risks using the same quantitative figures or the same business risks under different financial-statement figures. For example, the ratio of working capital to total assets can be the same for different businesses with different risks or different for businesses with the same risks. Previous studies have demonstrated the existence of earnings management using accounting figures (Dechow *et al* (1996); Burgstahler and Dichev (1997); Teoh *et al* (1998); and Hoffman and Patton (2002)). Furthermore, because of the asymmetric practice of recording losses and gains in financial reporting (ie, conservatism[1]), accounting figures can vary with the degree of a firm's position on the use of asymmetric recognition of earnings and losses (Basu (1997)). Therefore, without certain adjustments to the accounting figures, the application of a Z-score could generate several different sets of Z-scores for the same types of business risk. In this sense, we need to adjust the Z-score to make it comparable across firms.

We follow the accruals approach taken by previous studies in the accounting literature (Healy (1985); Dechow *et al* (1996); and Teoh *et al* (1998)) in order to calculate how much earnings deviate from the expected financial-reporting figures if they are subject to manipulation. We then reconstruct the Z-score based on the abnormal accruals[2] adjustments and verify how much distortion is exhibited by the

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[1] Accounting conservatism is the practice of recognizing all probable losses/expenditures as they are discovered/incurred but deferring the recognition of revenue until it is verified.

[2] Abnormal accruals not only reflect the quality of earnings but also capture the influence of accounting policy. Previous literature documents that the probability of litigation increases as income-increasing accruals occur (Lys and Watts (1994)).

Z-score. We apply this adjusted Z-score to measure the degree of deviation from the bankruptcy probability for the bankruptcy and nonbankruptcy sample. We find that, overall, the Z-score is overstated (ie, underestimates bankruptcy probability) for the income-increasing earnings-management case, while it is understated (ie, overestimates bankruptcy probability) for the income-decreasing earnings-management case. The magnitude of bias due to earnings distortion is statistically significant and it underestimates the bankruptcy probability by about 15%. When we apply the same adjustment to the bankruptcy firms, we find that the adjusted bankruptcy probability is 78% for the income-increasing earnings-management case, while it is only 31% for the unadjusted probability. This result demonstrates that, without the adjustment for the income-increasing case, the bankruptcy prediction will cause significant levels of type I error (classified as no bankruptcy prediction for the bankrupt firms). Thus, this study shows the importance of understanding change in accounting attributes and proposes a way to adjust for such changes in the application of the Z-score. These results confirm that there is a bias in the bankruptcy prediction models, as demonstrated in another study by Beaver *et al* (2009). Beaver *et al* (2009) did not offer solutions for such bias; we believe that our study is the first to propose a new method for calculating an adjusted Z-score measure. Furthermore, we investigate whether the weights imposed on the prediction factors should also be adjusted given the adjustments on the factors. After adopting the earnings-management-adjusted predictors, we find that the weights should also be revised to provide a more accurate prediction of bankruptcy.

This study contributes to the literature by applying the Z-score in a more sophisticated firm environment and by providing more accurate Z-score predictability in terms of bankruptcy testing. The adjusted model is also of great importance to auditors, since auditors often use accruals-related information in decision-making contexts. Among the different uses of Z-scores, auditors use the Z-score extensively to evaluate audit risk (Choi *et al* (2004); Fargher and Jiang (2008); Blay *et al* (2011); and Catanach *et al* (2011)). After the passing of the Sarbanes–Oxley Act (hereafter referred to as SOX), auditors started to focus more on audit quality, becoming more conservative with regard to compliance issues with clients. Large audit firms are less likely to tolerate poor accrual quality. Therefore, the adjusted Z-score model is aligned with the conservative practices of auditors, and the use of the earnings-manipulation-adjusted Z-score model helps auditors to evaluate the audit risk in their risk assessment procedure better. Finally, the globalization of accounting standards also calls for a revolution of the Z-score. As regulation begins to shift toward the IFRS regime, proper financial-statement fundamentals become more crucial. If the Z-score is to help creditors and investors to make sound credit-rating decisions, it is important that the Z-score model reflects any changes in the underlying accounting attributes. Our study demonstrates how the use of an accounting-attributes-adjusted

Z-score model can help in detecting potential bias in the Z-score. This, in turn, provides guidelines on how to facilitate the global Z-score users in their decision making. In contrast with previous studies, we adopt a specific adjustment to apply to the Z-score as a new measure for bankruptcy prediction.

This paper is organized as follows. Section 2 discusses the accounting components of the Z-score. Section 3 proposes a new model to adjust for changes in accounting attributes. Empirical results are presented in Section 4 to compare the differences in the prediction power of bankruptcy between the original unadjusted Z-score and our adjusted Z-score. Section 5 summarizes and concludes.

2 ACCOUNTING DISTORTION AND ALTMAN'S Z-SCORE

Altman's Z-score is widely used to measure the bankruptcy probability. Furthermore, it has a variety of applications in industry practice and academia as a representative credit risk measure. Although there are several variants of the Z-score model, the industry standard form calculation based on financial statements and stock prices is as follows:

$$Z\text{-score} = 1.2T_1 + 1.4T_2 + 3.3T_3 + 0.6T_4 + 0.999T_5 \tag{2.1}$$

where:

$$\begin{aligned}
T_1 &= \text{working capital/total assets} \\
T_2 &= \text{retained earnings/total assets} \\
T_3 &= \text{earnings before interest and taxes/total assets} \\
T_4 &= \text{market value of equity/total liabilities} \\
T_5 &= \text{sales/total assets}
\end{aligned}$$

As demonstrated in the formula, the Z-score is constructed to increase when the liquidity improves and/or earnings (or sales revenue) increase. Thus, a higher Z-score means a higher level of liquidity and earnings, and can be interpreted as having a smaller probability of bankruptcy. On the other hand, a lower Z-score translates into a higher probability of bankruptcy. Put into accounting terms, an increase in current assets, earnings or sales would lead to a higher Z-score, which means a lower probability of bankruptcy.

2.1 Changes in accounting attributes

While financial statements are a major source for credit analyses or risk assessments such as the Z-score, the attributes of financial statements have changed drastically in recent years. In particular, two distinctive events greatly changed the financial-reporting environment: SOX (in 2002) and the IFRSs.

Since the enactment of SOX, public accounting firms have been under great scrutiny, with tightened standards in the application of generally accepted accounting principles (GAAPs) to their clients with regular reviews by a new agent called the Public Company Accounting Oversight Board. Due to the increased audit risk, the new enactment induces accounting firms to act very conservatively in their audit procedures. In other words, accounting firms have become reluctant to allow their clients much room for discretionary decisions (Cahan and Zhang (2006) and Chang *et al* (2009)). On the other hand, the SOX enactment has introduced great information asymmetry. Prior to SOX, public information on audit quality was limited, which meant earnings boostings were possible. However, in the post-SOX era, firms have had a tendency to adjust earnings downward to reflect conservative auditors' positions (Higgs and Skantz (2006)). Thus, the new regulatory enactment and firms' reactions to the new regulation all lead to distortions of accounting figures.

Along with these regulatory changes, the worldwide turn to globalization has gradually led to the harmonized accounting standards of the IFRSs. One aspect of this harmonization of accounting standards is principle-based accounting, which involves fair market value. Another is estimation-based accounting, which requires significant professional judgments. However, this new accounting paradigm has the potential to generate several different sets of financial statements for the same business transaction. DeFond (2010) argues that the implementation of such paradigm changes may increase the likelihood of managers and auditors using their discretion when applying IFRSs relative to US GAAPs.[3] Furthermore, due to the recent collapse of the global financial system, investors are very sensitive to economic indicators that can easily distort traditional accounting recording principles. As a result, applying a conventional Z-score with financial-statement information that does not reflect accounting attributes properly may mislead creditors or investors. With diversified accounting figures as a result of using a different set of accounting principles, it has become difficult to maintain homogeneous risk measures. The Z-score is no exception to these environmental changes, and it deserves attention in order to make it more useful.

2.2 Distortion of the Z-score

As noted previously, the Z-score relies on accounting figures. Therefore, any changes in accounting recording may cause a distortion in the Z-score. Most firms are likely to prefer an increase in the Z-score due to capital market incentives. Some examples

[3] This increased discretion is described as not providing users with implementation guidance.

of accounting changes that would increase Z-score (lowering the probability of bankruptcy) are as follows.

(1) Sales increase with credit:

- current ratio increase.

(2) Underestimation of expenses:

- earnings and retained earnings increase.

(3) Overstate equity by

- recording positive special items,
- deferring the recognition of asset impairment,
- classifying capital lease as operating lease.

These elements of financial reporting are fairly prevalent among US firms. This is documented in the accounting and finance literature (Cohen and Zarowin (2010); Bhojrar *et al* (2009); and McVay (2006)). With these potential distortions in fundamental accounting figures, the Z-score is unlikely to be comparable across firms and years.

2.3 Illustration of distortion

As illustrated in the example in Table 1 on page 96, the Z-score can be distorted upward as accounting practices such as credit sales increase. While a new increase in credit sales significantly lowers bankruptcy probability, an increased receivables account reflected in increased current assets will ultimately make the business more risky due to the increased uncertainty with the receivable collection. Unless there is an adequate adjustment of the Z-score to reflect the increased business risk, using the unadjusted Z-score without reflecting the traits of financial statements will greatly distort credit risk ratings.

3 ADJUSTED Z-SCORE

3.1 Adjusted Z-score bankruptcy model

In reality, we do not observe exactly which accounts are affected by earnings management or various estimation methods of accounts in financial reporting. Thus, it is almost impossible to adjust a Z-score to its distortion-free level. However, previous studies on earnings management provide us with tools to estimate the potential distortion amount in earnings. Thus, we can use this estimated earnings-management amount to adjust a Z-score so that it is as close as possible to its pre-distortion level.

Since the distortion amount mostly affects earnings figures and will eventually be reflected by retained earnings and total assets, the proposed adjusted Z-score equation would be as follows:

$$\begin{aligned}\text{adjusted } Z\text{-score}\\ &= 1.2 \times ((\text{working capital} - \text{EM})/(\text{total assets} - \text{EM}))\\ &\quad + 1.4 \times ((\text{retained earnings} - \text{EM})/(\text{total assets} - \text{EM}))\\ &\quad + 3.3 \times ((\text{earnings before interest and taxes} - \text{EM})/(\text{total assets} - \text{EM}))\\ &\quad + 0.6 \times (\text{market value of equity}/\text{total liabilities})\\ &\quad + 0.999 \times ((\text{sales} - \text{EM})/(\text{total assets} - \text{EM})) \qquad (3.1)\end{aligned}$$

where EM is the estimated earnings-management distortion amount.

As noted in the formula, it is likely that Z-scores will be reduced when the increased earnings portion is adjusted.[4] This means that the firms that distort their accounting figures upward are likely to bias their Z-score upward. As a result, many potentially bankrupt firms hide from the sight of creditors or investors by sending incorrect information, recording a lower bankruptcy probability than should be the case. By adjusting for this wrong information, our model enhances the usefulness of the Z-score.

3.2 Calculation of adjustment: earnings management

To calculate EM, the required adjustment of accounting figures used in the above adjustment formula, we derive the residuals by following the estimation model of Dechow *et al* (1996), Collins (2002) and Kothari *et al* (2005). First, we calculate the total accruals before adjustment as follows:

$$\text{TA}_{it} = \text{EBXI}_{it} - \text{CFO}_{it} \qquad (3.2)$$

where:

$$\begin{aligned}\text{TA}_{it} &= \text{total accruals for firm } i \text{ in year } t\\ \text{EBXI}_{it} &= \text{earnings before extraordinary items for firm } i \text{ in year } t\\ \text{CFO}_{it} &= \text{cashflow from operations for firm } i \text{ in year } t\end{aligned}$$

Then we run the following regression to obtain the predicted value of total accruals by year, industry and return on assets decile:

$$\text{TA}_{it} = \beta_0 + \beta_1(\Delta\,\text{Sales}_{it} - \Delta\,\text{AR}_{it}) + \beta_2\,\text{PPE}_{it} + \varepsilon_{it} \qquad (3.3)$$

[4] This is because most firms record less than 100% return on assets.

TABLE 1 Illustration of the distortion of Z-scores. [Table continues on next page.]

(a)

Balance sheet	Before distortion
Current asset	10 000
Noncurrent asset	100 000
Total assets	110 000
Current liability	10 000
Noncurrent liability	70 000
Common capital	1 500
Retained earnings	6 800
Net income	11 700
Total liability and equity	100 000

(b)

Income statement	Before distortion
Sales	100 000
Cost of goods sold (60%)	–60 000
Gross margin	40 000
SGA	–20 000
Income before interest and taxes	20 000
Interest expense	–2 000
Pretax income	18 000
Tax expense	–6 300
Net income	11 700

In addition, the stock price is US$5 per share with 5000 shares outstanding. Current bankruptcy probability: Z-score = 1.78; probability of bankruptcy = 22%. “SGA” stands for selling, general and administrative expense.

where:

$$\begin{aligned}\Delta\,\text{Sales}_{it} &= \text{change in sales revenue for firm } i \text{ in year } t\\ \Delta\,\text{AR}_{it} &= \text{change in accounts receivables for firm } i \text{ in year } t\\ \text{PPE}_{it} &= \text{plant and equipment for firm } i \text{ in year } t\end{aligned}$$

TABLE 1 Continued.

(c)

Balance sheet	After distortion
Current asset	50 000
Noncurrent asset	100 000
Total assets	150 000
Current liability	24 000
Noncurrent liability	70 000
Common capital	1 500
Retained earnings	6 800
Net income	37 700
Total liability and equity	140 000

(d)

Income statement	After distortion
Sales	200 000
Cost of goods sold (60%)	−120 000
Gross margin	80 000
SGA	−20 000
Income before interest and taxes	60 000
Interest expense	−2,000
Pretax income	58 000
Tax expense	−20 300
Net income	37 700

Earnings management: sales are doubled via relaxed credit criteria for sales activities. Some adjustments are made to be consistent with the increase in sales. Z-score and bankruptcy probability after the distortion: Z-score = 3.02; bankruptcy probability = 2.2%. "SGA" stands for selling, general and administrative expense.

Finally, the earnings-management (EM) portion, often also called abnormal accruals, is defined as follows:

$$\mathrm{EM}_{it} = \mathrm{TA}_{it} - [b_0 + b_1(\Delta\,\mathrm{Sales}_{it} - \Delta\,\mathrm{AR}_{it}) + b_2\,\mathrm{PPE}_{it}] \tag{3.4}$$

where the b values are the parameter estimates from Equation (3.3).

TABLE 2 Sample selection: year coverage from 1999 to 2010.

All observations	95 947
Data available for the estimation of earnings management	47 570
Data without adjusted Z-score[a]	1 672
Sample used for analysis	45 898
Earnings-increasing case	21 337
Earnings-decreasing case	24 561
Total bankruptcy cases	1 380
Data available for adjusted Z-score	469
Earnings-increasing case	227
Earnings-decreasing case	242

[a]Adjusted Z-scores for these observations are unavailable (they correspond to the observations in the top and bottom 1% of the extreme value of the variables used in our earnings management estimation). Particularly when income-increasing earnings management is estimated to be 100% or higher, the corresponding adjusted Z-score becomes unavailable because adjusted denominators used for Z-score calculation become zero or negative, thereby generating unusable adjusted Z-scores.

4 EMPIRICAL TEST

4.1 Sample and descriptive statistics

To detect the degree of bias in the Z-score, we use all of the available data for the years 1999–2010 from Standard & Poor's Research Insight. From the initial sample of 47 570 with data available for the estimation of Z-scores and abnormal accruals, we exclude 1672 observations for which we cannot calculate the usable adjusted Z-scores.[5] The sample selection is shown in Table 2.

Among these observations, there are a total of 21 337 with income-increasing earnings management and 24 561 with income-decreasing earnings management. For further analysis of bankruptcy cases, we identify firms with bankruptcy notification (1380 observations) and 469 bankrupt firm-years are identified for which we can calculate both Z-scores and earnings management during the years before bankruptcy notification. Among this bankruptcy sample, 227 observations are income-increasing earnings-management cases, and 242 observations are income-decreasing earnings-management cases.

Table 3 on the facing page shows the basic statistics and correlation coefficients among our test variables.

[5] We exclude the top and bottom 1% of the individual variables for which we cannot obtain usable adjusted Z-scores. For example, the boundary values of discretionary accruals are earnings increases of more than 150% or earnings decreases of more than 100% of total assets. For these values we cannot calculate the adjustment value for the factors used in the Z-score.

TABLE 3 Descriptive statistics and correlation coefficients: 45 898 observations for the years 1999–2010.

(a) Sample descriptions

	Mean	Standard deviation	25%	Median	75%
Z-score	2.023	2.334	1.047	2.157	3.307
Adjusted Z-score	2.030	2.376	1.006	2.203	3.356
Abnormal accruals	−0.145	0.755	−0.072	−0.007	0.054

(b) Correlation coefficients

	Z-score	Adjusted Z-score
Adjusted Z-score	0.845*	—
Abnormal accruals	0.141*	−0.166*

An asterisk denotes significance at the 1% level.

Part (a) of Table 3 shows that the mean value of the Z-score is almost the same as the adjusted Z-score: the former is 2.02 (with bankruptcy probability of 15.4%), while the latter is 2.03 (with bankruptcy probability of 15.2%). The slight increase in adjusted Z-score is mainly due to the negative abnormal accruals (−14.5% of total assets at the beginning of the fiscal year). This confirms an upward adjustment of Z-scores.

Part (b) of Table 3 presents the correlation coefficients. The Z-score has a positive association with abnormal accruals (0.141 and significance at the 1% level), while the adjusted Z-score has a negative correlation with abnormal accruals (−0.166 and significance at the 1% level). This suggests that, as earnings are managed upward, the Z-score will be biased upward.

4.2 Comparison of the Z-score: before and after adjustment

To test our conjecture on the direction of earnings management, we divide the sample into income-increasing abnormal accruals and income-decreasing abnormal accruals. Part (a) of Table 4 on the next page shows the test statistics for the income-increasing and income-decreasing cases.

In the income-increasing cases, we find that the original Z-score is on average 2.326, while the corresponding adjusted Z-score using our model is 1.622. The difference is about 0.704 in Z-score, with statistical significance at the 1% level. For the income-decreasing case, the adjusted Z-score becomes 2.386, which is 0.627 higher

TABLE 4 Comparison of Z-scores and probability of bankruptcy before and after adjustment for earnings management: all firm-years of 45 898 observations for years 1999–2010.

(a) Comparison of Z-scores

	Z-score before adjustment (A)	**Z-score after adjustment (B)**	**Difference ($A - B$)**
Earnings-increasing case	2.326	1.622	0.704
t-statistics	(162.365)	(92.517)	(80.515)
Earnings-decreasing case	1.759	2.386	−0.627
t-statistics	(110.441)	(174.724)	(−98.899)

(b) Comparison of probability of bankruptcy

	Probability before adjustment (%)	**Probability after adjustment (%)**
Earnings-increasing case	9.24	26.70
Earnings-decreasing case	22.39	8.29

than the original Z-score. This difference is statistically significant at the 1% level. This confirms that income-increasing (respectively, decreasing) earnings management biases the Z-score upward (respectively, downward).

Part (b) of Table 4 shows the average bankruptcy probability based on the results from Z-scores and corresponding adjusted Z-scores. The results show that type I error of bankruptcy prediction[6] increases if the Z-score is not adjusted. On average, the bankruptcy probability with adjusted Z-score increases by 17.46% (from 9.24% to 26.7%) for firms managing earnings upward, while the chance of bankruptcy decreases by 14.10% (from 22.39% to 8.29%) for firms choosing to manage earnings downward. Overall, the results suggest that both type I and type II errors increase due to earnings management.

Table 5 on the facing page shows similar results when we exclude the bankrupt firm observations from the sample. In both income-increasing and income-decreasing cases, the distortion is slightly smaller (17.15% and 13.89%). Comparing the sample size of nonbankruptcy cases (45 429) with the bankrupt cases (469), the differences suggest that bankruptcy firm observations aggravate the distortion of Z-scores.

[6] Here, a type I error is one that misclassifies a firm with a high chance of bankruptcy probability as less likely to go bankrupt.

TABLE 5 Comparison of Z-scores and probability of bankruptcy before and after adjustment for earnings management: nonbankrupt firm-years of 45 429 observations for years 1999–2010.

(a) Comparison of Z-scores

	Z-score before adjustment (A)	**Z-score after adjustment (B)**	**Difference ($A-B$)**
Earnings-increasing case	2.335	1.636	0.698
t-statistics	(162.688)	(93.309)	(79.981)
Earnings-decreasing case	1.769	2.392	−0.624
t-statistics	(110.888)	(174.752)	(−98.595)

(b) Comparison of probability of bankruptcy

	Probability before adjustment (%)	**Probability after adjustment (%)**
Earnings-increasing case	9.09	26.24
Earnings-decreasing case	22.09	8.20

4.3 Bankruptcy sample case

Next we apply the same tests to the bankruptcy sample. The results are presented in Table 6 on the next page.

Part (a) of the table shows the test statistics for the income-increasing and income-decreasing cases. In the income-increasing cases, we find that the original Z-score is 1.501 on average, while the corresponding adjusted Z-score is 0.244. The difference is about 1.257 in Z-score and is statistically significant at the 1% level, which is more significant than the general case presented in Table 4 on the facing page. For the income-decreasing case, the original Z-score is 0.757, while the adjusted Z-score becomes 1.743. The difference is 0.986 higher than the original Z-score and is statistically significant at the 1% level. The biases in both directions are more exaggerated than the full sample tests.

Panel (b) of Table 6 on the next page presents the corresponding bankruptcy probability based on the results from Z-scores and the corresponding adjusted Z-scores. For the income-increasing earnings-management case, the bankruptcy probability becomes 77.52% after adjustments, compared with the preadjustment probability of 30.82%. This indicates that the bankruptcy probability is understated for more than 45% in the absence of the adjustment. On the other hand, for the income-decreasing earnings-management case, the bankruptcy probability is overstated by 59.6% before

TABLE 6 Comparison of Z-scores and probability of bankruptcy before and after adjustment for earnings management: bankruptcy firm-years of 469 observations for the years 1999–2010.

(a) Comparison of Z-scores

	Z-score before adjustment (A)	**Z-score after adjustment (B)**	**Difference ($A - B$)**
Earnings-increasing case	1.501	0.244	1.257
t-statistics	(8.814)	(1.136)	(10.120)
Earnings-decreasing case	0.757	1.743	−0.986
t-statistics	(3.838)	(10.696)	(−9.979)

(b) Comparison of probability of bankruptcy

	Probability before adjustment (%)	**Probability after adjustment (%)**
Earnings-increasing case	30.82	77.52
Earnings-decreasing case	59.60	22.87

adjustment, compared with 22.87% after adjustment. However, the interpretation of the income-decreasing case may not be as clear as its income-increasing counterpart. The reason for this is that bankruptcy samples typically start with losses in business operations; therefore, we should be cautious in using Z-score adjustment for the income-decreasing case.

4.4 Comparison of bankruptcy prediction

Finally, to measure the performance of the adjusted Z-score, we apply the logit regression model for the whole sample and compare the bankruptcy prediction accuracy between the unadjusted Z-score and the adjusted Z-score:

$$\text{prob}(\text{bankruptcy}_{it}) = \lambda_0 + \lambda_1(Z\text{-score}_{it} \text{ or adjusted } Z\text{-score}_{it}) + \text{error}_{it} \quad (4.1)$$

where $\text{bankruptcy}_{it} = 1$ if it belongs to the bankruptcy firm-year, and 0 otherwise, and the Z-scores are as defined previously.

By running Equation (4.1) for each bankruptcy prediction score (ie, Z-score and adjusted Z-score), we can measure which one performs better.

Table 7 on the facing page shows the test results of our comparison of two bankruptcy prediction measures (Z-score and adjusted Z-score). The estimates of

TABLE 7 Comparison of Z-score and adjusted Z-score for bankruptcy prediction: all firm-years of 45 898 observations for the years 1999–2010.

	Model 1: before adjustment (χ^2)	**Model 2: after adjustment (χ^2)**
λ_0	–4.445* (7441.355)	–4.256* (5889.721)
λ_1 for Z-score	–0.084* (40.790)	—
λ_1 for adjusted Z-score	—	–0.209* (80.409)
Proportion of correct bankruptcy classification	43.0%	53.2%

Model: prob(bankruptcy$_{it}$) $=\lambda_0+\lambda_1$(Z-score$_{it}$ or adjusted Z-score$_{it}$) $+$ error$_{it}$, where bankruptcy$_{it}$ $=1$ if it belongs to the bankruptcy firm-year, and 0 otherwise, and the Z-score and adjusted Z-score measures are as defined previously. The model is for the data with adjusted Z-score available where income-decreasing adjustment is less than 100% of total assets when positive earnings management occurs and the results are similar to a maximum likelihood estimation model that adjusts for heteroskedasticity. An asterisk denotes significance at the 1% level.

the coefficients on Z-score and adjusted Z-score are both negative and statistically significant at 1%.[7]

This indicates that both measures are useful in predicting bankruptcy risk and that a lower score leads to a higher probability of bankruptcy. However, the coefficient on the adjusted Z-score (–0.209) is lower than its unadjusted counterpart (–0.084). This suggests that the prediction power of the adjusted Z-score is better than the conventional Z-score would provide. Consistent with the difference in coefficients, we then find that the prediction accuracy rate from applying the adjusted Z-score is 53.2%, compared with 43% when the unadjusted Z-score is used. This test further confirms our argument that, without proper adjustments of the accounting attributes for the conventional Z-score, the inference drawn from applying an unadjusted Z-score may be biased.

4.5 Additional analyses on weights of discriminant factors

The above analyses suggest that there might have been a shift in the weights in the original Altman model. To verify the potential shift, we replicate the original discriminant analysis and compare weights and prediction accuracy. First, we match

[7] The logit analysis is only performed for the data after the adjustment where income-decreasing adjustment is less than 100% of total assets when positive earnings management occurs. Since the adjusted denominators used for Z-score calculation become zero or negative, adjusted Z-scores become unavailable. In addition, when we use a maximum likelihood estimator that makes statistical adjustments for heteroskedasticity, the results are similar.

TABLE 8 Comparison of weights on discriminant factors and bankruptcy prediction: 252 matched observations for the years 2003–10.

	Altman	Original factor	Adjusted factor
X_1	1.2	0.353	−0.005
X_2	1.4	1.016	0.734
X_3	3.3	−1.455	1.440
X_4	0.6	0.393	0.383
X_5	0.999	−0.122	−0.206
Posterior bankruptcy prediction accuracy			
Cutoff point 0.15		80%	84%
Cutoff point 2.67		50%	51%
Accuracy for the holdout sample			
Cutoff point 0.15	42%	67%	72%
Cutoff point 2.67	48%	52%	52%

See (4.2). The results presented in the "Posterior bankruptcy prediction accuracy" section are based on the total bankruptcy classification accuracy. The accuracy levels are higher when only bankruptcy firms are used in the calculation. Please note that the Posterior accuracy rate for the Altman weights is not available because the sample period is different from Altman's (1968) original model.

the bankruptcy observations from our new accounting regulation period of 2003–10 to the nonbankrupt pool by year, industry and size. We then run the discriminant analysis for a set of factors used in Altman's model. Next, we run the same model using our adjusted factors. The discriminant function used for these two sets of factors is:

$$\begin{aligned}\text{D score} = {} & X_1 \times (\text{working capital}/\text{total assets (or adjusted)}) \\ & + X_2 \times (\text{retained earnings}/\text{total assets (or adjusted)}) \\ & + X_3 \times (\text{earnings before interest and taxes}/\text{total assets (or adjusted)}) \\ & + X_4 \times (\text{market value of equity}/\text{total liabilities (or adjusted)}) \\ & + X_5 \times (\text{sales}/\text{total assets (or adjusted)}) \end{aligned} \tag{4.2}$$

where $X_1, \dots, X_5$ are weights on the discriminant factors.

We run the above model with original and adjusted factors as defined in Equation (3.1). Table 8 shows the weight comparison and prediction accuracy.

The second column in Table 8 shows the Altman (1968) factor loadings. The third and fourth columns provide the weights derived from the Altman model using our sample period from 2003 to 2010 and weights derived by using original factors and earnings-management-adjusted factors, respectively. We observe that the weights for the Altman original factors also change. There are changes in both the magnitude and the sign. For example, the weights on earnings (X_3) and size-adjusted sales (X_5) are both negative in the third column. This sign switch for earnings (X_3), for example, implies that the more earnings are recorded, the more likely it is that the company will go bankrupt. This contradicts conventional wisdom and evidence from the real world. However, as shown in the last column, when we use the adjusted earnings factor, the weight becomes positive, which is consistent with Altman's model and intuition.[8] The weight on working capital (X_1) becomes negative in the model of adjusted factors. It suggests that the increase in working capital does not necessarily lead to a higher Z-score. Such increases in working capital may be due to the strategic timing of investment, sales and financing decisions.

Table 8 on the facing page also provides the bankruptcy prediction accuracy for the in-sample analysis and the holdout sample. It is clear that the discriminant analysis using the earnings-management-adjusted factors provides the most accurate bankruptcy prediction. The model improves the prediction accuracy from 80% to 84% (and from 67% to 72% for the holdout sample) when we apply the cutoff point of 0.15.[9] When we applied Altman's cutoff point, 2.67, all three models seems to be at the similar level (48–52%).[10] This further confirms the usefulness of our adjusted Z-score model and the need for the adjustment of the existing bankruptcy prediction weights on the predictors. The results also suggest that we should reconsider the mapping from the discriminant score (the Z-score in Altman) to bankruptcy probability (the choice of cutoff point).

5 SUMMARY AND CONCLUSION

One of the main tools used in credit risk rating among analysts is Altman's Z-score for the prediction of bankruptcy. Following its proposal in the 1960s, the Z-score has become widely accepted by many different practitioners. Therefore, the accuracy and predictability of the tool for calculating bankruptcy probabilities is of ultimate importance to its users. The calculation of conventional Z-scores is based on financial statements and stock prices, and its formula relies heavily on accounting attributes. This raises the concern that a shift in accounting attributes would affect the effectiveness of the Z-score. Specifically, changes in the accounting attributes make it

[8] The sign switch for the earnings-management-adjusted sales (X_5) factor may be explained by the fact that the increase in sales alone does not lead to a decrease in the probability of bankruptcy. Moreover, the negative weight for X_5 is not significantly different from zero.
[9] The cutoff point was chosen to maximize the bankruptcy prediction accuracy (minimizing the sum of type I and type II errors).
[10] When we calculate the prediction accuracy for the bankrupt firms only, the accuracy can be maximized to 100% with the cutoff point of 2.67 but the accuracy of Altman's original weighting score only achieves 94%.

difficult to compare and obtain objective ratings across firms. In particular, the practice of earnings management and the decrease in the use of earnings management after the passage of SOX have had significant impacts on how accounting figures are prepared. Therefore, the fundamentals used to calculate the Z-score have shifted dramatically. As illustrated in Table 1 on page 96, when earnings are manipulated (or when the same business transactions are recorded in different accounting methods), the Z-score is biased.

We adjusted for such bias by using a statistical model of earnings-management detection, so that the bias caused by accounting practices is quantified. We then compared the adjusted Z-score with Altman's unadjusted Z-score to test the degree of bias in the calculations of Z-scores. In general, we found that there is a significant upward bias in the income-increasing earnings manipulation that reduces the bankruptcy probability from 27% to 9%. In the bankruptcy sample, it was notable that income-increasing earnings management reduced the bankruptcy probability from 78% to 31%. In addition, we found that the adjusted Z-score performed better at bankruptcy prediction than the traditional Z-score. In the additional analysis, we found that the factors in the Z-score needed to be reconstructed and we demonstrated that our adjusted factors performed better in the prediction of bankruptcy cases. These results show that the adjusted Z-score should be used as proposed in this study in order to obtain the correct credit ratings. On the other hand, for the income-decreasing cases, the bankruptcy probability was overstated by 22% before adjustment, instead of 8% after adjustment. We also observed similar results in the bankruptcy sample. Nevertheless, the income-decreasing cases should be interpreted more cautiously, since the conservative nature of accounting recognizes losses more readily than earnings. This conservatism of accounting practice has been confounded by the increased conservatism of audit quality controls by the Public Company Accounting Oversight Board since the enactment of SOX. Nonetheless, managers tend to manage earnings downward in order to reserve a "cookie jar" or in order to take a "big bath" at the opportune moment to create cushions for future earnings manipulation. Z-scores are more biased downward when earnings are manipulated in such circumstances than they are due to negotiations with auditors to deliver more conservative accounting figures. More sophisticated further studies are necessary to determine the necessary level of adjustment for Z-scores in credit ratings.

Firms choose to manage earnings for different reasons, and the literature documents a few of these. Firms manage earnings upward to either meet/beat analysts' forecasts (Burgstahler and Dichev (1997)) or to self-serve a management's compensation/bonus scheme (Healy (1985)); firms manage earnings downward to take a big bath or to reserve cookie jars; firms may also choose to manage earnings to convey private information regarding managers' expertise and to reduce information asymmetry (Demski (1998)). This paper mainly focuses on the first two rationales for earnings management. The third motivation for earnings management is of great interest, but is beyond the scope of this paper. However, a future area of research could be to investigate such comprehensive Z-score models. Moreover, the extended studies should also refine the adjustment, incorporating further adjustments for asymmetric financial reporting as influenced by conservatism.

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