ARTICLE IN PRESS
PACFIN-00811; No of Pages 17
Pacific-Basin Finance Journal xxx (2016) xxx–xxx

Contents lists available at ScienceDirect

Pacific-Basin Finance Journal

journal homepage: www.elsevier.com/locate/pacfin

# Modeling default prediction with earnings management

Hsiou-Wei William Lin [a], Huai-Chun Lo [b], Ruei-Shian Wu [c,*]

[a] Department of International Business, Tunghai University, Taiwan; Department of International Business, National Taiwan University, Taiwan
[b] Finance Discipline, College of Management, Innovation Center for Big Data and Digital Convergence, Yuan Ze University, Taiwan
[c] Accounting Discipline, College of Management, Yuan Ze University, Taiwan

ARTICLE INFO

*Article history:*
Received 9 June 2015
Received in revised form 19 January 2016
Accepted 22 January 2016
Available online xxxx

*Keywords:*
Accrual-based earnings management
Default prediction model
Real earnings management

ABSTRACT

This study explores whether taking into account real earnings management improves specification of the default prediction model based on the Z-score methodology for Chinese listed companies. We demonstrate that the model proposed by Altman (1968) overestimates (underestimates) the Z-score and thus the survival probability for firms engaging in aggressive (minor or no) income-increasing manipulation. By contrast, our inclusion of the indicator variable for real earnings management considerably enhances the explanatory power of Z-score factors for firm survival/default. With respect to the ability to predict out-of-sample default, our findings suggest that the accounting-based credit scoring model adjusted for real earnings management unanimously yields a greater prediction accuracy rate and a lower false loan rejection rate than the unadjusted scoring model for financially non-distressed firms.


## 1. Introduction

This study examines whether and how taking account of earnings management improves specification of the default prediction model based on the scoring methodology proposed by Altman (1968) for Chinese listed companies. Collecting reported accounting measures including working capital, retained earnings, earnings before interests and tax expenses, leverage ratios, and assets turnover, the Altman model derives the Z-score using either fixed or sample-specific weights of the determinants that are assigned by the estimated coefficients, regardless of the quality of earnings. Specifically, the greater the Z-score is, the lower the probability of bankruptcy becomes. However, prior to financial distress, firms may have strong incentives to reduce expenditures or even strategically engage in earnings management. Consequently, accounting-based determinants retrieved from financial statements may be biased factors for credit risk.

Let us consider the following example of real earnings management prior to financial distress to address the importance of adjusting accounting-based default prediction models. Firms may use discounts, pre-loading schemes, or extended payment dates exclusively to increase reported revenues. As a result, the ratio of sales revenue to total assets, which serves as a variable in the scoring model, may be boosted, but the operating cash flows may increase at a slower rate than for the revenues. The sales increases for these firms may thus fail to indicate strong future profitability but raise the Z-score and lower the predicted default likelihood in the Z-score model. Such a notion is consistent with the findings of Graham et al. (2005), who interviewed more than 400 executives, among whom approximately 78% admit that they prefer meeting or exceeding earnings benchmarks at the expense of long-run performance.

To explore the extent of the distortion of accounting-based models caused by earnings manipulation, this study incorporates measures of real earnings management activities to allow weights of the determinants to vary with the deviation of the sales, production, and spending activities from the norm. We then examine whether our adjusted model enhances the performance

* Corresponding author at: Accounting Discipline, College of Management, Yuan Ze University, No. 135, Yuan-Tung Road, Chung-Li District, Taoyuan City 32003, Taiwan. Tel.: +886 3 4638800x2195; fax: +886 3 4630377.
*E-mail addresses:* plinhw@thu.edu.tw (H.-W.W. Lin), hclo@saturn.yzu.edu.tw (H.-C. Lo), rswu@saturn.yzu.edu.tw (R.-S. Wu).

http://dx.doi.org/10.1016/j.pacfin.2016.01.005

of the out-of-sample default prediction. Consistently, we find that, compared with predictions generated by our adjusted Z-score model, both the Z-score and the survival probability derived from the unadjusted Z-score model are overestimated for firms that excessively reduce expenses or accelerate sales recognition. By contrast, the Z-score and the survival probability derived from the unadjusted model are both underestimated for other firms. With respect to the out-of-sample default predictability, our findings suggest that real earnings management measures help explain the Z-score model coefficient estimates, and thus the corresponding adjustment considerably enhances the predictive power of the Z-score methodology.

Our study contributes to the literature in two ways. First, it shows that the differences in earnings quality among firms can help determine the usefulness of the accounting-based Z-score model, which is widely adopted to assess credit risk. Second, we include real earnings management variables and notably enhance the specification of the default prediction model based on the Z-score methodology. Specifically, without adjustments, the Z-score model appears to overestimate the default likelihood for firms engaging in aggressive real earnings management, but underestimates the default likelihood for other firms. With the failure to take into account the effect of real earnings management on the default prediction, the survival probability is overestimated by 4.53% for firms with aggressive real earnings management and is underestimated by 3.26% for firms with lower real earnings management, consistent with the contention that there is a need to adjust accounting-based default prediction models. The differences are unanimously negative for the group of firms with more pronounced earnings management measures. Our findings may be applied to the practice of loan pricing.

The remainder of this study is organized as follows: Section 2 reviews the related literature. Section 3 develops our hypotheses. Section 4 describes the research design and our proposed adjustment for default prediction models. Section 5 presents the findings and the out-of-sample prediction results. Section 6 concludes.

## 2. Literature review

Our study relates to (i) research that develops default prediction models and the out-of-sample predictability for the models and (ii) research on firms' revenue and/or expense management. In the following discussion, we review studies of default prediction methodologies and real activity earnings management.

### *2.1. Default prediction model*

Over the last 40 years, credit risk scholars have explored effective methodologies for predicting borrowers' default or business failure. Influential steps in this field include those made by Beaver (1967) and Altman (1968), whose accounting-based models adopt financial ratios to predict business failures. By employing 14 financial ratios to classify an individual firm's failure against a matched sample, Beaver adopts a dichotomous classification test to identify the error rates that a potential creditor would experience. Altman, in contrast, develops a multiple discriminant analysis (MDA) method to solve the inconsistency problem related to Beaver's univariate model. Altman adopts 22 potentially useful financial ratios to detect default for his sample manufacturing firms, among which one-half file a bankruptcy petition. He then selects 5 ratios among the 22 that provide the best overall power to predict corporate bankruptcy.[1] These five variables concern liquidity, profitability, leverage, solvency, and activity ratios. Credit risk studies commonly apply Altman's MDA (Altman et al., 1977, 1995; Blum, 1974; Deakin, 1972; Edmister, 1972; Eisenbeis, 1977; Gombola et al., 1987; Lussier, 1995; Micha, 1984; Piesse and Wood, 1992; Taffler and Tisshaw, 1977). However, most of the aforementioned studies observe that the basic assumptions of MDA are often violated.

To address the problems associated with MDA, Ohlson (1980) proposes a conditional logit model. The practical advantages of the conditional logit model are that no assumptions are required. Therefore, Ohlson examines samples consisting of both bankrupt and non-bankrupt firms using seven financial ratios and two binary variables. The resulting prediction accuracy is lower than that of MDA (Altman, 1968; Altman et al., 1977). However, following Ohlson's (1980) pioneering work, researchers largely adopt logit models to predict default (Altman and Sabato, 2007; Aziz et al., 1988; Becchetti and Sierra, 2002; Gentry et al., 1985; Keasey and Watson, 1987; Mossman et al., 1998; Ooghe et al., 1995; Platt and Platt, 1990; Zavgren, 1983). The binary dependent variable indicates whether a firm's default inherently fits well in the logistic regression. A result between zero and one yielded by the logistic regression is practically useful because it directly suggests a probability of default of a diagnosed target. The estimated coefficients also provide meaningful information regarding the influence of each independent variable on the default prediction.

An alternative to accounting-based default prediction models such as those of Altman and Ohlson is the price-based prediction model, which adopts information from the stock market to assess financial distress. Building upon the bond pricing model proposed by Merton (1974), the KMV Corporation develops a default prediction model, called the KMV-Merton model. In the corporation's setting, the equity of a firm is modeled as a call option on the underlying firm value with a strike price equal to the accounting book value of the firm debt. Because neither the underlying value of the firm nor its volatility is readily observable, the model assumes that both may be inferred from the equity value, stock return volatility and several other observable variables by solving two simultaneous nonlinear equations. The model then specifies the default probability as a normal cumulative density function of a computed distance to default depending on the firm's underlying value, volatility, and book value of debt.

[1] The five financial ratios used in the unadjusted *Z*-score model proposed by Altman (1968) are (i) working capital/total assets, (ii) retained earnings/total assets, (iii) EBIT/total assets, (iv) market value of equity/book value of total debt, and (v) sales/total assets.

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005

The accounting-based default prediction models differ from the price-based models primarily in the critical factor adopted to predict firm default. Unlike models based on capital market prices, accounting models use items in firm financial statements and thus may be affected by real earnings management. In an efficient market, investors undo the effects of earnings manipulation and incorporate them into the pricing process. Therefore, the model used in this study adjusts for the effect of earnings management in the accounting-based models, instead of using a capital market pricing approach.

### *2.2. Real earnings management measures*

We adopt the real earnings measures to identify firms that may engage in or avoid earnings manipulation through real transactions. Specifically, Gunny (2010) proposes four types of real earnings management: (i) myopically investing in research and development (R&D); (ii) myopically investing in selling, general, and administrative expenditures; (iii) controlling the timing of long-term asset and investment disposition; and (iv) increasing discounts to accelerate sales or production to reduce production costs per unit. Roychowdhury (2006) argues that managers boost earnings primarily through sales manipulation, discretionary expenses reduction, or overproduction. Specifically, by providing customers with substantial discounts, firms may boost their reported revenues but decrease their operating cash flows. Moreover, firms that reduce discretionary expenses experience an increase in net income and earnings per share. Firms may also reduce the cost of goods sold (COGS) to increase earnings. Thus, firms may overproduce goods to decrease the unit cost of goods available for sale because overproduction reduces fixed costs per unit. Roychowdhury (2006) and Gunny (2010) both find that real earnings management has a significantly negative effect on future performance.

Several studies investigate real earnings management around certain corporate events. For example, Cohen and Zarowin (2010) focus on seasoned equity offerings. The authors use the measures of real-activity earnings management proposed by Roychowdhury (2006), including abnormal operating cash flow, production costs, and discretionary expenses, which are the sum of SG&A, R&D, and advertising expenses, documenting that real earnings management has a negative impact on firm value. Collectively, real-activity earnings management significantly changes the numbers reported in the financial statement and jeopardizes firm value in subsequent accounting periods.

## 3. Hypothesis development

The risk assessment model proposed by Altman (1968) evaluates firms' credit risk by adopting accounting variables. However, the literature reiterates the existence of accounting number manipulation. We conjecture that considering the aforementioned potential distortions helps enhance the predictive power of the model. Specifically, we investigate whether real earnings management for operation, production, and spending activities affects the specification of the adjusted risk assessment model. We assess the significance of each explanatory factor in the adjusted model and the model predictive power. The information content of financial reporting may be greater and more precise after controlling real transactions for earnings management, and the adjusted risk assessment model may be more efficient in detecting firms' financial distress. Therefore, we conjecture that the adjusted risk assessment model is better specified and has better predictive power when incorporating at least one of the impacts of real earnings management. We develop the following hypotheses for inclusion of the effects of abnormal cash flows from operating activities, production cost, and discretionary expenditure:

**Hypothesis 1.** The risk assessment model becomes better specified and has greater predictive power after incorporating abnormal cash flow from operating activities, which proxies for real earnings management.

**Hypothesis 2.** The risk assessment model becomes better specified and has greater predictive power after incorporating abnormal production cost, which proxies for real earnings management.

**Hypothesis 3.** The risk assessment model becomes better specified and has greater predictive power after incorporating abnormal discretionary expenditure, which proxies for real earnings management.

## 4. Research designs for estimating the effect of earnings management on the effectiveness of the risk assessment model

### *4.1. Real earnings management*

This study adopts the real earnings management measures developed by Cohen et al. (2008) and Roychowdhury (2006), taking three forms of real transaction manipulations into account: acceleration of recognizing sales, reporting of lower COGS through increased production, and decreases in discretionary expenses. They are estimated, respectively, as

$$\frac{\mathrm{CFO}_{i,t}}{\mathrm{A}_{i,t-1}} = \mathrm{k}_1 \frac{1}{\mathrm{A}_{i,t-1}} + \mathrm{k}_2 \frac{\mathrm{SALE}_{i,t}}{\mathrm{A}_{i,t-1}} + \mathrm{k}_3 \frac{\Delta\mathrm{SALE}_{i,t}}{\mathrm{A}_{i,t-1}} + \varepsilon_{i,t}, \tag{1}$$

$$\frac{\mathrm{ProdCost}_{i,t}}{\mathrm{A}_{i,t-1}} = \mathrm{k}_1 \frac{1}{\mathrm{A}_{i,t-1}} + \mathrm{k}_2 \frac{\mathrm{SALE}_{i,t}}{\mathrm{A}_{i,t-1}} + \mathrm{k}_3 \frac{\Delta\mathrm{SALE}_{i,t}}{\mathrm{A}_{i,t-1}} + \mathrm{k}_4 \frac{\Delta\mathrm{SALE}_{i,t-1}}{\mathrm{A}_{i,t-1}} + \varepsilon_{i,t}, \tag{2}$$

$$\frac{\mathrm{DiscEXP}_{i,t}}{\mathrm{A}_{i,t-1}} = k_1 \frac{1}{\mathrm{A}_{i,t-1}} + k_2 \frac{\mathrm{SALE}_{i,t-1}}{\mathrm{A}_{i,t-1}} + k_3 \frac{\Delta\mathrm{SALE}_{i,t}}{\mathrm{A}_{i,t-1}} + k_4 \frac{\Delta\mathrm{SALE}_{i,t-1}}{\mathrm{A}_{i,t-1}} + \varepsilon_{i,t}, \tag{3}$$

where CFO denotes operating cash flows; SALE represents sales revenue; ΔSALE is defined as the change in sales revenue; Prod is the sum of COGS and the change in inventory during the year, indicative of production cost; and DiscEXP denotes discretionary expenses, including advertising expenditures, R&D expenses, and SG&A. The coefficient is estimated for the same industry during the same year for Eq. (1) through Eq. (3), and the coefficient estimated for the industry for year $t-1$ is introduced into the data for company $i$ during year $t$ to derive the expected value. We compute the abnormal value by using the actual value less the expected value as the proxy for real earnings management. The abnormal CFO (AbCFO) is a measurement of the acceleration of recognizing sales through increased price discounts or more lenient credit terms. We use abnormal production costs (AbProdCost) and abnormal discretionary expenses (AbDiscEXP) to gauge the presence of earnings management in the form of cost reduction, perhaps at the expense of future profits.

### 4.2. Empirical model and variable measurements

This study refers to the five factor components with respect to the Z-score in the construction of the predictive model for financial distress to explore how individual factors help explain financial distress. The unadjusted Z-score regression model is as follows:

$$\mathrm{P}\left(\mathrm{Normal}_{i,t} = 1\right) = \beta_0 + \beta_1 \mathrm{ZWC}_{i,t-1} + \beta_2 \mathrm{ZRE}_{i,t-1} + \beta_3 \mathrm{ZEBIT}_{i,t-1} + \beta_4 \mathrm{ZLEV}_{i,t-1} + \beta_5 \mathrm{ZATO}_{i,t-1} + \varepsilon_{i,t}, \tag{4}$$

where Normal is a dummy variable that equals 0 when the sample firm suffers financial distress during year $t$ and 1 otherwise. The greater these five explanatory variables become, the less likely it is that financial distress will occur. Specifically, ZWC denotes working capital, ZRE denotes retained earnings, ZEBIT denotes earnings before interests and tax expenses, ZLEV denotes financial leverage (defined as the market value of equity over the book value of debts), and ZATO denotes sales. All independent variables except ZLEV are deflated by total assets. In this forecast model, to detect financial distress, all independent variables are for year $t-1$, which also helps predict whether the sample company experiences financial distress during year $t$. To avoid the situation in which financial distress surfaces before the release of the financial reports for the previous year, we define year $t$ as the period from the financial reporting date for year $t-1$ to the next reporting date for the dependent variable. Given that the dependent variable is a binary dummy variable, Eq. (4) is a logistic regression model.

To investigate whether adjustment for real transactions adds to the explanatory power of the Z-score over financial distress, we incorporate interaction terms between earnings management proxies and Z-score factors. The adjusted Z-score regression model with the variables of earning management is follows:

$$\begin{aligned}\mathrm{P}\left(\mathrm{Normal}_{i,t} = 1\right) = {} & \beta_0 + \beta_1 \mathrm{ZWC}_{i,t-1} + \beta_2 \mathrm{ZRE}_{i,t-1} + \beta_3 \mathrm{ZEBIT}_{i,t-1} + \beta_4 \mathrm{ZLEV}_{i,t-1} + \beta_5 \mathrm{ZATO}_{i,t-1} + \gamma_1 \mathrm{DZWC}_{i,t-1} \\ & + \gamma_2 \mathrm{DZRE}_{i,t-1} + \gamma_3 \mathrm{DZEBIT}_{i,t-1} + \gamma_4 \mathrm{DZLEV}_{i,t-1} + \gamma_5 \mathrm{DZATO}_{i,t-1} + \varepsilon_{i,t},\end{aligned} \tag{5}$$

where the five independent variables, different from the ones for Eq. (4), are the products of the extent of earnings management and each of the five Z-score factors. For instance, $\mathrm{DZWC} = \mathrm{D} \times \mathrm{ZWC}$, where dummy variable D equals 1 when the proxy measure for earnings-increasing manipulation of a firm-year observation exceeds a certain threshold level. Specifically, for tests based on studies finding that the greater the abnormal production costs are, the more pronounced upward real earnings management is, we adopt abnormal production cost as the proxy for upward earnings management, setting dummy variable D to equal 1 when AbProdCost is within the top 10% in year $t-1$ and 0 otherwise. By contrast, for tests adopting abnormal CFO or abnormal discretionary expenses to proxy upward earnings management, the dummy variable D equals 1 when AbCFO or AbDiscEXP is within the bottom 10% in year $t-1$ and 0 otherwise. Such a design with respect to these two abnormal measures is consistent with the notion that the lower the estimates of abnormal CFO or abnormal discretionary expenses are, the greater the upward real earnings management may be. To ensure robustness, we alternately adopt 10% and 25% thresholds to identify firms with significant real earnings management for the financial distress forecasting model.

### 4.1. Data source and sample criteria

Our sample consists of companies that ceased to be publicly listed and firms that became public from 2000 to 2012. We retrieve that financial statement data of all publicly listed companies in China from 2000 to 2012 from China Stock Market Accounting Research (CSMAR).[2] For our 2001 to 2012 accuracy tests, we retrieve accounting data from 2000 to 2011 to compute the financial ratios by using accounting measures at the beginning of each fiscal year. Moreover, we collect data regarding financial distress from both Wind Information and the Taiwan Economic Journal and then manually classify various crisis events by

[2] The sample period starts from 2000 because the distress event data for the publicly listed companies in China before 2000 are not authorized for use from the Wind Information database.

reviewing descriptions of the events. Financially distressed companies are identified as those (i) with their assets frozen or seized, (ii) filing bankruptcy or restructuring, or (iii) with their core businesses in a distressed status. A total of 79 listed Chinese companies are identified as firms suffering from financial distress during our sample period.[3] Panel A of Fig. 1 shows the distribution of the number of distressed firms throughout the sample period. In 2004, 13 companies are financially distressed, the highest during the period, whereas in 2011, 2 companies are in financial distress, the lowest in the period. Compared with the previous decade, the number of companies reporting financial distress declines after 2010.

For firms experiencing financial distress, nevertheless, management is likely to eliminate certain SG&A expenditures. Within the SG&A category, the literature identifies advertising expenditures, R&D expenditures, and SG&A as the accounts subject to real earnings management. However, the databases do not provide advertising expenses as a separate item. Moreover, R&D spending is a separate item in the databases but with a large number of missing values. Therefore, we refer to this aggregate SG&A measure as a proxy for discretionary expenses.

Panel A of Table 1 summarizes the industry distribution of distressed versus non-distressed firms over the 12-year sample period. Industry classification is based on the CSMAR, which includes the data of 2661 listed companies in China. A total of 79 companies are classified as distressed, accounting for 2.97% of all CSMAR firms. The remaining 2582 companies are not subjected to financial distress. Among these observations, we form our research sample by excluding (i) firms within two highly regulated or protected industries, specifically, finance and properties sectors; (ii) universities, government offices, and government-owned enterprises; and (iii) firm-year combinations with missing values.

Panel A of Table 1 shows that the majority of listed companies in China in our sample are industrial firms. The manufacturing sector has the most firms in financial distress, 42 companies. However, conglomerates report the highest percentage of companies in financial distress at 5.13%. The financial industry has no companies in financial distress, indicating China's tight control over the industry and its determination to ensure the confidence of investors and the public in the financial system. Only one real estate company suffers financial distress, an indication of the booming development of the real estate market in China throughout the sample period and the relative financial strength of the industry.

Panel B of Table 1 summarizes the ownership breakdown of distressed firms. Most of these companies are controlled by individuals. Specifically, 3.04% of the individually controlled firms and 2.97% of overall companies suffer financial distress. The second largest category is state-owned enterprises under the State-Owned Assets Supervision and Administration Commission (SASAC) of the State Council, which includes 577 companies. Among these, 2.53% (15 firms) are distressed. This percentage is lower than the overall average. A large proportion of owners of the listed companies have close ties with the Chinese government, and these companies may be controlled by state-owned enterprises, government agencies, or local governments. In China, government agencies control certain listed companies, which thus typically become tasked with maintaining social stability and implementing government policies. As a result, these firms rarely experience financial stress. None of the central government-owned companies has ever disclosed any financial difficulty.

Taking into account the unique nature of the financial industry and the scarcity of financial troubles in the Chinese real estate industry over the sample period, we eliminate these two industries from the sample. Moreover, we remove special-mission-tasked, government-related companies (central government-owned enterprises, government agencies, local governments, local state-owned enterprises, and universities). Quite a few companies struggle with financial difficulties but remain ongoing concerns for a few years after experiencing their first financial distress event. Therefore, for each distressed firm, this study identifies its initial financial distress event but excludes its subsequent years. The comparison group consists of all of the companies within the same industry during the year of financial distress.

We gather a finalized sample of 54 financially distressed companies after eliminating those with missing values for the test variables. Panel B of Fig. 1 presents the number of firms with financial distress by year. Panel B of Table 1 shows the industry and ownership of the final sample in our study. The sample distribution is largely in line with all of the listed companies in China. A total of 1276 listed companies in the sample have never suffered any financial distress, and we find that 4.06% of the full sample experience financial difficulty, with a percentage greater than 2.97%, the mean among all of the listed companies in China.

### 4.2. 4.5. Descriptive statistics

We winsorize all continuous variables at 1% and 99%. Table 2 presents the 7362 firm-year observations that meet the aforementioned criteria. The mean and median Z-score measures are 3.58 and 2.38, respectively. The mean working capital (ZWC), mean retained earnings (ZRE) and mean EBIT (ZEBIT), as percentages of total assets, are 7.2%, 1.9%, and 3.1%, respectively, all less than 10%. Sales are, on average, 70.08% of total assets (ZATO = 0.7008). The market value of equity is approximately 4.5 times total liabilities (ZLEV = 4.5). The average return on assets (ROA) and return on equity (ROE) are 3.24% and 5.85%, respectively. The debt ratio (DebtR) is approximately 52%. The mean total assets of the sampled companies is 5213 million yuan (approximately 1035 million US Dollars), yet the median is 1.7 million yuan, implying a right skewness of the asset distribution, and a few outlier companies have fairly large assets. Specifically, the mean is even greater than the third quartile (P75). In terms of real earnings management, both mean AbCFO and mean AbDiscEXP are slightly greater than zero, but mean AbProdCost

[3] CSMAR also provides financial data for pre-IPO firms. However, these pre-IPO firms do not experience financial distress before their IPOs. Moreover, the quality of financial statements for pre-IPO firms may not be identical to that of publicly traded firms. Therefore, this study focuses on the sample of exchange-listed firms.

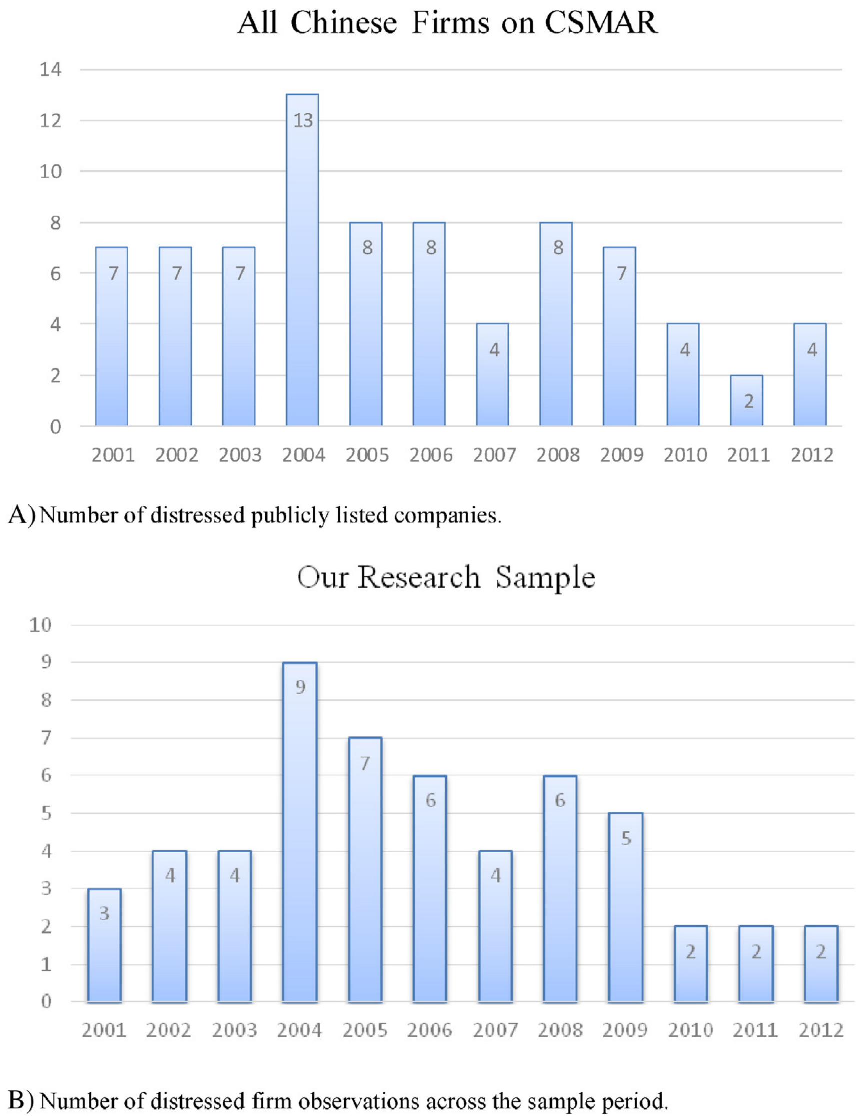


**Fig. 1.** Number of Chinese distressed firms by year. Panel A. Number of distressed publicly listed companies. Panel B. Number of distressed firm observations across the sample period.

is negative. Both mean and median discretionary accruals (DA) are approximately zero, in line with the theoretical value. All of the medians of the variables regarding real earnings management are trivial, consistent with theory.

Table 3 reports both means and medians for all variables to further compare the characteristics of distressed firms and non-distressed firms. Both mean and median Z-scores of the distressed firms are significantly less than those of the non-distressed firms, with some even trending below zero. The five Z-score factors of distressed firms are also significantly less than those of the non-distressed firms, indicating the warning power of Z-scores for financial difficulties. Regarding ROA and ROE, distressed firms, on average, experience losses during the year before financial difficulties. For these firms, the mean debt ratio (DebtR) exceeds 80%. All of these numbers differ significantly from those of the non-distressed firms, except for firm size (Size). Firm size for distressed firms is greater than that of non-distressed firms on average; however, the difference is significant only for the median.

Among the real earnings management variables, both mean and median abnormal cash flows from operating activities of distressed firms are negative and are significantly less than those of non-distressed firms. This result supports the notion that firms tend to time the recognition of sales prior to the financial distress events. As a result, their CFOs are less than the estimates derived from the comparison group. Moreover, mean abnormal production costs of distressed firms are positive and greater than those of non-distressed firms, indicating that distressed firms tend to report lower COGS through increased production, to boost their earnings. In general, the AbDiscEXPs of distressed firms are greater than those of non-distressed firms. However, the difference in median does not reach the 10% significance level.

**Table 1**
Distribution of distressed versus non-distressed firms by industry and ultimate controlling party.

| | All Chinese firms on CSMAR | | | Full research sample | | |
|---|---|---|---|---|---|---|
| | Distressed firm | Non-distressed firm | Distressed percentage | Distressed firm | Non-distressed firm | Distressed percentage |
| *Panel A: Industry distribution* | | | | | | |
| Finance | 0 | 41 | 0.00 | | | |
| Public utility | 7 | 199 | 3.40 | 5 | 121 | 3.97 |
| Properties | 1 | 142 | 0.70 | | | |
| Conglomerates | 22 | 407 | 5.13 | 18 | 165 | 9.84 |
| Industrials | 42 | 1612 | 2.54 | 25 | 887 | 2.74 |
| Commerce | 7 | 181 | 3.72 | 6 | 103 | 5.50 |
| Total | 79 | 2582 | 2.97 | 54 | 1276 | 4.0 |
| *Panel B: Distribution of the entity's ultimate controlling party* | | | | | | |
| University | 1 | 13 | 7.14 | | | |
| Central-state-owned enterprise | 0 | 33 | 0.00 | | | |
| Central-government office | 1 | 40 | 2.44 | | | |
| Provincial-government | 1 | 91 | 1.09 | | | |
| Provincial-state-owned enterprise | 1 | 27 | 3.57 | | | |
| Provincial SASAC | 15 | 577 | 2.53 | 13 | 480 | 2.64 |
| Others | 4 | 28 | 12.50 | 3 | 21 | 12.50 |
| Individual investor | 40 | 1277 | 3.04 | 34 | 475 | 6.68 |
| SASAC | 4 | 297 | 1.33 | 2 | 243 | 0.82 |
| Collectively run enterprise | 0 | 16 | 0.00 | 0 | 11 | 0.00 |
| Off-shore investor | 3 | 83 | 3.49 | 2 | 40 | 4.76 |
| Employees | 1 | 6 | 14.29 | 0 | 6 | 0.00 |
| No information | 8 | 94 | 7.84 | | | |
| Total | 79 | 2582 | 2.97 | 54 | 1276 | 4.06 |

Notes: This table reports the distribution of distressed and non-distressed firms by industry and ultimate controlling party. Panel A presents the number of companies by industry. Panel B presents the number of companies by the entity's ultimate controlling party. SASAC represents State-owned Assets Supervision and Administration Commission of the State Council.

## 5. Empirical results

### 5.1. Effect of earnings management on the Z-score model

To investigate the extent to which earnings management explains the slope coefficients of the factors in the Altman's Z-score model for financial distress, we estimate the regression coefficients of the five distress forecasting factors both with and without incorporating the interaction terms for earnings management, as shown in Tables 4 and 5, respectively. Table 4 reports that, except for ZWC, the estimated coefficients for the data sample are largely the same as the Z-score coefficients reported by Altman (1968). Specifically, the coefficient is the greatest for ZEBIT and the lowest for ZLEV. Moreover, with the exception of ZWC, the factors exhibit 5% statistical significance.

**Table 2**
Summary statistics.

| Variable | Mean | Median | Min. | Q1 | Q3 | Max. | Std. dev. |
|---|---|---|---|---|---|---|---|
| Z-score | 3.5818 | 2.3786 | −7.1227 | 1.3449 | 4.1655 | 51.6289 | 4.6885 |
| ZWC | 0.0720 | 0.0763 | −0.9184 | −0.0705 | 0.2227 | 0.7452 | 0.2289 |
| ZRE | 0.0191 | 0.0508 | −0.9874 | 0.0047 | 0.0993 | 0.5047 | 0.1718 |
| ZEBIT | 0.0310 | 0.0325 | −0.4932 | 0.0073 | 0.0665 | 0.3074 | 0.0799 |
| ZLEV | 4.5321 | 2.2945 | 0.0176 | 1.0823 | 4.9422 | 85.0425 | 7.2473 |
| ZATO | 0.7008 | 0.5838 | 0.0278 | 0.3726 | 0.8782 | 4.5777 | 0.4905 |
| ROA | 0.0324 | 0.0314 | −0.4458 | 0.0085 | 0.0642 | 0.4462 | 0.0791 |
| ROE | 0.0585 | 0.0663 | −1.5256 | 0.0189 | 0.1258 | 1.3185 | 0.1917 |
| DebtR | 0.5197 | 0.5124 | 0.0424 | 0.3804 | 0.6347 | 2.6688 | 0.2298 |
| Size | 5213.11 | 1722.86 | 20.39 | 942.49 | 3553.46 | 1,656,368.00 | 31,005.29 |
| AbCFO | 0.0067 | 0.0082 | −0.3290 | −0.0379 | 0.0551 | 0.3094 | 0.0860 |
| AbProdCost | −0.0124 | −0.0097 | −0.4788 | −0.0604 | 0.0391 | 0.6722 | 0.1096 |
| AbDiscEXP | 0.0110 | 0.0043 | −0.2212 | −0.0225 | 0.0372 | 0.3671 | 0.0669 |

Notes: This table presents the descriptive statistics, with Min., Q1, Q3, Max., and Std. dev. representing the minimum, first quartile, third quartile, maximum, and standard deviation, respectively. The sample includes 7362 observations. We derive the Z-score according to Altman (1968). ZWC is the ratio of working capital to total assets. ZRE is the ratio of retained earnings to total assets. ZEBIT is the ratio of earnings before interest and taxes to total assets. ZLEV is the ratio of market value of equity to book value of liabilities. ZATO is the ratio of sales revenue to total assets. ROA is return on assets. ROE is return on equity. DebtR is debt ratio. Size is total assets in million yuans. AbCFO is abnormal operating cash flows. AbProdCost is abnormal production costs. AbDiscEXP is abnormal discretionary expenses.

**Table 3**
Differences in mean and median between distressed and non-distressed firms.

| Variable | Mean | | | | Median | | | |
|---|---|---|---|---|---|---|---|---|
| | Distressed firm | Non-distressed firm | Difference | $t$ | Distressed firm | Non-distressed firm | Difference | $Z$ |
| Z-score | −0.3261 | 3.6107 | −3.9368 | −6.16*** | −0.0580 | 2.3953 | −2.4533 | −9.39*** |
| ZWC | −0.2382 | 0.0742 | −0.3123 | −9.67*** | −0.2143 | 0.0773 | −0.2916 | −6.63*** |
| ZRE | −0.2391 | 0.0205 | −0.2596 | −9.35*** | −0.1251 | 0.0511 | −0.1762 | −6.74*** |
| ZEBIT | −0.1141 | 0.0320 | −0.1461 | −13.56*** | −0.0695 | 0.0330 | −0.1025 | −8.74*** |
| ZLEV | 1.5491 | 4.5541 | −3.0050 | −3.04*** | 1.1562 | 2.3069 | −1.1508 | −5.19*** |
| ZATO | 0.4337 | 0.7028 | −0.2691 | −4.02*** | 0.3407 | 0.5853 | −0.2446 | −5.17*** |
| ROA | −0.1153 | 0.0335 | −0.1487 | −13.95*** | −0.0782 | 0.0317 | −0.1099 | −8.88*** |
| ROE | −0.3531 | 0.0609 | −0.4140 | −14.32*** | −0.2902 | 0.0667 | −0.3570 | −7.46*** |
| DebtR | 0.9561 | 0.5165 | 0.4395 | 14.19*** | 0.8345 | 0.5114 | 0.3231 | 9.13*** |
| Size | 1693.32 | 5239.12 | −3545.80 | −0.84 | 932.45 | 1726.92 | −794.47 | −4.29*** |
| AbCFO | −0.0280 | 0.0070 | −0.0349 | −2.98*** | −0.0242 | 0.0085 | −0.0327 | −3.96*** |
| AbProdCost | 0.0160 | −0.0126 | 0.0286 | 1.91* | 0.0236 | −0.0098 | 0.0335 | 2.52** |
| AbDiscEXP | 0.0304 | 0.0108 | 0.0196 | 2.15** | 0.0120 | 0.0043 | 0.0077 | 1.35 |

Notes: This table compares test results for distressed firms versus non-distressed firms, with respect to mean and median measures. We present $t$- and Wilcoxon rank sum $Z$-statistics for tests of differences in mean and median, respectively. The sample includes 7362 observations. We derive the Z-score according to Altman (1968). ZWC is the ratio of working capital to total assets. ZRE is the ratio of retained earnings to total assets. ZEBIT is the ratio of earnings before interest and taxes to total assets. ZLEV is the ratio of market value of equity to book value of liabilities. ZATO is the ratio of sales revenue to total assets. ROA is return on assets. ROE is return on equity. DebtR is debt ratio. Size is total assets (in million yuans). AbCFO is abnormal operating cash flows. AbProdCost is abnormal production costs. AbDiscEXP is abnormal discretionary expenses. DA is discretionary accrual. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

**Table 4**
Regression results of Z-score model.

| Variable | Altman (1968) | Not controlled for year effect | | Controlled for year effect | |
|---|---|---|---|---|---|
| | | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ |
| Intercept | | 3.9536 | 138.59*** | 3.7421 | 110.65*** |
| ZWC | 1.20 | 0.2985 | 0.20 | 0.2167 | 0.11 |
| ZRE | 1.40 | 0.5451 | 2.76* | 0.7235 | 4.56** |
| ZEBIT | 3.30 | 6.2846 | 24.14*** | 5.9607 | 18.23*** |
| ZLEV | 0.60 | 0.2323 | 6.97*** | 0.2795 | 8.40*** |
| ZATO | 0.99 | 1.1797 | 7.13*** | 1.2616 | 7.83*** |
| R-square | | 0.0174 | | 0.0187 | |
| N | | 7362 | | 7362 | |

Notes: This table shows the results of estimating the logistic regression model of Eq. (4). The sample includes 7362 observations. ZWC is the ratio of working capital to total assets. ZRE is the ratio of retained earnings to total assets. ZEBIT is the ratio of earnings before interest and taxes to total assets. ZLEV is the ratio of market value of equity to book value of liabilities. ZATO is the ratio of sales revenue to total assets. $\chi^2$ is the chi-square statistic for logistic regression estimated coefficient, Est. coeff. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

Panel A of Table 5 shows whether the acceleration of recognizing sales to boost revenue affects the specification of the default prediction model. Regardless of the inclusion of year effects, abnormal CFO exhibits a significantly positive effect on the slope coefficient for the ratio of retained earnings to total assets (DZRE) and a negative effect on the coefficient for asset turnover (DZATO) for both the 10% and 25% thresholds for earnings management. Specifically, taking into account the real activities of increasing earnings by accelerating sale recognition emphasizes the effect on retained earnings to total assets because retained earnings is a permanent line item in the statement of financial position and is not heavily affected by the current sales, which is a temporary line item in the statement of comprehensive income. However, the negative coefficient of DZATO suggests that the predictive role of asset turnover is reduced for firms with acceleration of recognizing sales, and thus, the sum of the coefficient estimates of ZATO and DZATO is less than the coefficient of ZATO (e.g., $0.6745 < 2.0566$ for D10 and controlled fixed effect). Though unduly accelerating recognition of sales may help boost the reported revenues and earnings, such a move does not improve the probability of firm survival.[4] Thus, the predictive role of accelerating sale recognition is reduced. Specifically, the coefficients for the ratio of working capital to total assets (DZWC), the ratio of earnings before interest and taxes to total assets

[4] Because accelerating recognition of sales increases both the numerator and denominator of asset turnover, such real activity manipulation may either increase the turnover ratio or decrease the ratio.

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005

**Table 5**
Regression results with adjustments for real earnings management.

| Variable | Not controlled for year effect | | | | Controlled for year effect | | | |
|---|---|---|---|---|---|---|---|---|
| | Threshold | | | | Threshold | | | |
| | D10 | | D25 | | D10 | | D25 | |
| | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ |
| *Panel A: Abnormal cash flows as the proxy for real earnings manipulation* | | | | | | | | |
| Intercept | 3.7527 | 118.67*** | 3.6959 | 111.59*** | 3.1278 | 9.11*** | 3.0693 | 8.78*** |
| ZWC | 0.9673 | 1.71 | 1.1597 | 1.65 | 0.8652 | 1.37 | 1.1061 | 1.51 |
| ZRE | 0.1788 | 0.24 | −0.3526 | 0.49 | 0.3525 | 0.86 | −0.2263 | 0.19 |
| ZEBIT | 6.0742 | 17.70*** | 7.7181 | 19.39*** | 5.6114 | 13.03*** | 7.4269 | 15.19*** |
| ZLEV | 0.2012 | 5.03** | 0.2141 | 3.91** | 0.2528 | 6.46** | 0.2598 | 4.86** |
| ZATO | 1.9633 | 11.41*** | 2.3337 | 10.82*** | 2.0566 | 11.99*** | 2.4252 | 11.32*** |
| DZWC | −2.4973 | 2.24 | −1.4952 | 1.22 | −2.2374 | 1.76 | −1.4629 | 1.22 |
| DZRE | 2.0098 | 5.50** | 1.6055 | 5.18** | 1.7131 | 3.78* | 1.6887 | 5.81** |
| DZEBIT | −2.2982 | 0.50 | −4.5223 | 2.78* | −1.4536 | 0.19 | −4.6466 | 2.69 |
| DZLEV | 0.1753 | 0.69 | 0.0396 | 0.07 | 0.1451 | 0.45 | 0.0380 | 0.06 |
| DZATO | −1.3455 | 4.19** | −1.4799 | 4.64** | −1.3821 | 4.20** | −1.4759 | 4.46** |
| R-square | 0.0191 | | 0.0193 | | 0.0203 | | 0.0208 | |
| *Panel B: Abnormal production costs as the proxy for real earnings manipulation* | | | | | | | | |
| Intercept | 3.9044 | 130.72*** | 3.8610 | 129.42*** | 3.1640 | 9.33*** | 3.1565 | 9.29*** |
| ZWC | 0.2243 | 0.11 | 0.9386 | 1.67 | 0.1848 | 0.08 | 0.8486 | 1.38 |
| ZRE | 0.5823 | 3.09* | 0.2998 | 0.70 | 0.7536 | 4.89** | 0.4990 | 1.85 |
| ZEBIT | 6.2655 | 23.53*** | 5.2741 | 13.19*** | 6.0170 | 18.20*** | 5.0043 | 10.28*** |
| ZLEV | 0.2175 | 6.33** | 0.1841 | 4.44** | 0.2670 | 7.89*** | 0.2292 | 5.73** |
| ZATO | 1.3251 | 7.90*** | 1.5049 | 8.61*** | 1.3794 | 8.31*** | 1.5927 | 9.16*** |
| DZWC | 7.7245 | 1.25 | −4.7640 | 6.08** | 7.5808 | 1.13 | −4.8397 | 6.30** |
| DZRE | −6.2935 | 0.83 | 1.8748 | 3.94** | −6.9057 | 0.98 | 1.7496 | 3.07* |
| DZEBIT | 5.3792 | 0.05 | 5.5429 | 2.59 | 6.8617 | 0.09 | 5.5130 | 2.39 |
| DZLEV | 2.1882 | 1.71 | 0.4557 | 2.67 | 2.0691 | 1.72 | 0.4630 | 2.56 |
| DZATO | −2.1289 | 3.57* | −0.6999 | 0.96 | −2.1724 | 3.58* | −0.7632 | 1.14 |
| R-square | 0.0183 | | 0.0188 | | 0.0197 | | 0.0200 | |
| *Panel C: Abnormal discretionary expense as a proxy for real earnings manipulation* | | | | | | | | |
| Intercept | 3.9754 | 130.62*** | 4.0578 | 139.43*** | 3.1952 | 9.54 *** | 3.2201 | 9.69*** |
| ZWC | 0.2685 | 0.14 | 0.2240 | 0.09 | 0.0617 | 0.01 | −0.0567 | 0.01 |
| ZRE | 0.2400 | 0.41 | 0.2060 | 0.27 | 0.4231 | 1.18 | 0.3998 | 0.89 |
| ZEBIT | 7.7497 | 32.64*** | 8.0186 | 32.97*** | 7.6490 | 26.65*** | 8.0435 | 27.77*** |
| ZLEV | 0.2705 | 6.89*** | 0.2376 | 5.46** | 0.3433 | 9.33*** | 0.3054 | 7.52*** |
| ZATO | 1.1672 | 5.87** | 1.1151 | 5.01** | 1.2611 | 6.52** | 1.1999 | 5.53** |
| DZWC | 0.3717 | 0.03 | 0.9310 | 0.37 | 0.9402 | 0.20 | 1.8908 | 1.49 |
| DZRE | 2.0047 | 4.21** | 1.5662 | 4.31** | 1.8803 | 3.78* | 1.2154 | 2.63 |
| DZEBIT | −13.8957 | 6.99*** | −12.0684 | 6.37** | −14.7276 | 8.25*** | −12.5837 | 6.84*** |
| DZLEV | 0.0006 | 0.00 | 0.0511 | 0.09 | −0.0457 | 0.05 | 0.0124 | 0.01 |
| DZATO | 0.0881 | 0.01 | 0.2224 | 0.10 | 0.1818 | 0.05 | 0.3096 | 0.18 |
| R-square | 0.0196 | | 0.0193 | | 0.0210 | | 0.0207 | |
| *Panel D: Proxy constructed by aggregating the three real activities measures* | | | | | | | | |
| Intercept | 3.9390 | 127.28*** | 3.9541 | 132.80*** | 3.1455 | 9.22*** | 3.0953 | 8.95*** |
| ZWC | 0.4335 | 0.36 | 0.2363 | 0.09 | 0.3008 | 0.17 | 0.0498 | 0.00 |
| ZRE | 0.1299 | 0.12 | 0.1857 | 0.22 | 0.2727 | 0.48 | 0.3155 | 0.56 |
| ZEBIT | 7.8237 | 32.72*** | 8.2381 | 32.73*** | 7.6494 | 26.40*** | 8.3398 | 27.29*** |
| ZLEV | 0.2728 | 6.85*** | 0.2439 | 5.41** | 0.3394 | 8.92*** | 0.3017 | 7.14*** |
| ZATO | 1.2445 | 6.18** | 1.4315 | 6.56** | 1.2988 | 6.47** | 1.4772 | 6.79*** |
| DZWC | −0.8946 | 0.21 | 0.4460 | 0.10 | −0.4127 | 0.04 | 0.9751 | 0.47 |
| DZRE | 2.5657 | 6.78*** | 1.1462 | 2.58 | 2.4686 | 6.45** | 0.9126 | 1.69 |
| DZEBIT | −13.3476 | 6.30** | −8.4544 | 5.54** | −13.8155 | 6.92*** | −8.5168 | 5.2** |
| DZLEV | −0.0160 | 0.01 | −0.0151 | 0.01 | −0.0736 | 0.15 | −0.0422 | 0.07 |
| DZATO | −0.0313 | 0.00 | −0.5279 | 0.76 | 0.1174 | 0.02 | −0.4794 | 0.61 |
| R-square | 0.0200 | | 0.0190 | . | 0.0214 | | 0.0201 | |

Notes: This table shows the results of estimating the logistic regression model of Eq. (5). The sample includes 7362 observations. ZWC is the ratio of working capital to total assets. ZRE is the ratio of retained earnings to total assets. ZEBIT is the ratio of earnings before interest and taxes to total assets. ZLEV is the ratio of market value of equity to book value of liabilities. ZATO is the ratio of sales revenue to total assets. The explanatory variables with the names that start with D represent the product of earnings management dummy variable and the respective five Altman scoring factors. For instance, DZWC = D × ZWC, where D equals 1 when the firm-year observation is with a proxy variable regarding the extent of earnings management being within the top 10% or top 25% and 0 otherwise. D10 and D25 represent the two different earnings management thresholds of 10% and 25%, respectively. $\chi^2$ is the chi-square statistic for estimated coefficient, Est. coeff., in logistic regression. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

(DZEBIT), and the leverage ratio (DZLEV) do not significantly differ from zero. Therefore, accelerating recognition of sales does not significantly affect the coefficients for DZWC, DZEBIT, and DZLEV. In sum, the results indicate that real earnings management by accelerating the recognition of sales affects the roles of retained earnings ratio and turnover factors in the Z-score model.

Panel B of Table 5 presents the extent to which manipulative reductions in COGS to boost earnings by firms affects the Z-score model in predicting firm distress. The findings show that the 10% and 25% thresholds for earnings management do not yield consistent results. Earnings management in the form of production cost reductions within the top 25% appears to negatively affect the explanatory power of working capital (DZWC) and positively affect that of retained earnings (DZRE) on firm survival. However, these results are not statistically significant with respect to the tests using the 10% threshold. We further explore the influence of manipulative reductions in COGS to boost earnings on working capital, which is the difference between current assets and current liabilities. If firms adopt a different inventory valuation method to shift COGS to ending inventory, current assets increase, in turn increasing working capital. If firms overproduce to boost earnings by reducing the unit cost, both current assets and current liabilities may increase. Specifically, the difference between the magnitude of increase in current assets and that in current liabilities depends on the payment terms and the extent to which firms engage in such real earnings management.

Panel C of Table 5 reports the effects of the reduction in discretionary expenses by firms to boost earnings on the predictive ability of the Z-score model. The results show that the reported earnings before interest and taxes of firms with greater discretionary expense play a less significant role in forecasting survival or distress, consistent with the notion that the unadjusted Z-score of distressed firms may be inflated. A cut-back in the SG&A increases concurrent earnings but may result in future profit reductions. Furthermore, earnings management in the form of reduced discretionary expenses positively affects the explanatory power of retained earnings. However, this coefficient is not stable. The coefficient of DZRE is no longer significant once year effects are incorporated.

We further follow Cohen et al. (2008) to compute an aggregate measure of real earnings, denoted REM, which combines the effects of AbCFO, AbProdCost, and AbDiscEXP. Panel D of Table 5 reports the extent to which aggregate real earning management explains the relationships between accounting explanatory variables and survival probability. The results are similar to those in Panel C. Collectively, compared with the estimates derived by the unadjusted Altman model in Table 4, the weight estimates of determinants in the Z-score model change when taking into account real earnings management.

Table 6 shows the differences in median Z-score and survival probability between unadjusted versus adjusted Z-scores. Panel A reports the percentage differences in Z-scores. The median unadjusted Z-score is 1.6683, which is computed from the coefficients reported in Table 4 without year effect. The median adjusted Z-score is computed from the coefficients reported in Table 5 without year effect. The percentage difference in Z-scores is computed by subtracting the adjusted Z-score from the unadjusted Z-score and then deflating the difference by the absolute adjusted Z-score. Taking as an example the results adopting the first 10% of AbCFO as the threshold of earnings management, the percentage difference in median Z-scores is 0.3019 when D equals 1, suggesting that the unadjusted Z-score is overestimated at the median by approximately 30% more than the adjusted Z-score by incorporating real earnings management. Conversely, the percentage difference in the median Z-score is −0.2023 when D equals 0, suggesting that the unadjusted Z-score is underestimated at the median by approximately 20% compared with the adjusted Z-score derived by incorporating real earnings management. When we take the 10% and 25% thresholds of AbProdCost, AbDiscEXP, and REM as the measures of real earnings management, the results are generally similar. Collectively, the unadjusted Z-score is overestimated (or underestimated) by more than the adjusted Z-score for firms engaging in (not engaging in) aggressive real earnings management.

We then compute the differences in survival probabilities between the unadjusted and adjusted Z-score models. Panel B of Table 6 shows that the median difference in survival probability differs significantly between the two Z-score settings. The median survival probability for the unadjusted model is 84.14%, which is estimated from the coefficients reported in Table 4 without year effect. Using AbCFO as an example, when we adopt 10% as the threshold for earnings management, the median difference in survival probability between the unadjusted and adjusted Z-score for firms with signs of income-increasing manipulations ($D = 1$) exceeds 4%. However, the median difference in survival probability is −3.74% for firms without signs of income-increasing manipulations ($D = 0$). That is, compared with the adjusted Z-score model, the unadjusted Z-score model overestimates the survival probability for firms with earnings management and underestimates the survival probability for firms with signs of income-increasing conduct. Regardless of the thresholds or the types of real earnings management measures we choose, the test results appear to be similar.

### *5.2. Out-of-sample predictions for financial distress*

We further explore the predictive power of the Z-score model that incorporates earnings management. Specifically, we perform out-of-sample logistic regression predictions, which constrain the predicted probabilities to the unit interval with a one-year horizon for financial distress, by introducing the estimated parameters from the five years of the estimation period in the absence of fixed effects into the sixth year; we then compare the predictions with the actual outcome. We adopt a moving estimation period of five years to derive the Z-score coefficients. The first five-year estimation period lies between 2001 and 2005, with its corresponding prediction period in 2006. The five-year window then moves one year later in sequence. A total of seven prediction years are recorded, from 2006 to 2012.

Table 7 shows the out-of-sample results related to survival probabilities and hit rates. Panel A reports the differences in survival probabilities between unadjusted versus adjusted Z-score models for the seven out-of-sample prediction years. The sample

**Table 6**
Differences in median Z-score and survival probability between unadjusted versus adjusted models.

| Sample | EM type | Threshold | D = 1 | | D = 0 | |
|---|---|---|---|---|---|---|
| | | | Median difference | SignRank | Median difference | SignRank |
| *Panel A: Percentage differences in Z-scores* | | | | | | |
| Full sample | AbCFO | 10% | 0.3019 | 92,229*** | −0.2023 | −10,280,000*** |
| | | 25% | 0.2269 | 615,980*** | −0.2977 | −7,429,548*** |
| | AbProdCost | 10% | 0.0942 | 54,402*** | −0.0020 | −16,357 |
| | | 25% | 0.4705 | 648,683*** | −0.2957 | −7,609,591*** |
| | AbDiscEXP | 10% | 0.1159 | 79,383*** | −0.0753 | −8,727,109*** |
| | | 25% | −0.0012 | −110,476*** | −0.0109 | −1,087,349*** |
| | REM | 10% | 0.1552 | 76,045*** | −0.1087 | −9,630,988*** |
| | | 25% | 0.2444 | 612,233*** | −0.1259 | −6,741,930*** |
| Distressed firms | AbCFO | 10% | 0.4679 | 14 | −0.2382 | −428*** |
| | | 25% | 0.1726 | 25 | −0.3067 | −213*** |
| | AbProdCost | 10% | −0.1620 | −1 | 0.0229 | 319*** |
| | | 25% | 0.2960 | 20 | −0.2107 | −207*** |
| | AbDiscEXP | 10% | 0.7706 | 8 | −0.0455 | −85 |
| | | 25% | 0.5366 | 14 | 0.0186 | 104 |
| | REM | 10% | 0.7881 | 7 | −0.0771 | −193** |
| | | 25% | 0.4306 | 18 | −0.0977 | −114 |
| Non-distressed firms | AbCFO | 10% | 0.2980 | 90,127*** | −0.2023 | −10,150,000*** |
| | | 25% | 0.2272 | 607,863*** | −0.2976 | −7,348,444*** |
| | AbProdCost | 10% | 0.0942 | 54,466*** | −0.0021 | −40,660 |
| | | 25% | 0.4709 | 641,294*** | −0.2958 | −7,517,306*** |
| | AbDiscEXP | 10% | 0.1150 | 78,159*** | −0.0754 | −8,668,467*** |
| | | 25% | −0.0014 | −106,261*** | −0.0110 | −1,103,480*** |
| | REM | 10% | 0.1535 | 74,897*** | −0.1088 | −9,543,929*** |
| | | 25% | 0.2443 | 605,387*** | −0.1261 | −6,686,807*** |
| *Panel B: Differences in survival probabilities* | | | | | | |
| Full sample | AbCFO | 10% | 0.0450 | 96,529*** | −0.0374 | −10,450,000*** |
| | | 25% | 0.0363 | 646,052*** | −0.0575 | −7,477,723*** |
| | AbProdCost | 10% | 0.0102 | 48,142*** | −0.0001 | −443,526*** |
| | | 25% | 0.0664 | 676,704*** | −0.0613 | −7,566,145*** |
| | AbDiscEXP | 10% | 0.0133 | 77,129*** | −0.0116 | −9,030,432*** |
| | | 25% | 0.0000 | 117,794*** | −0.0008 | −691,472*** |
| | REM | 10% | 0.0211 | 69,250*** | −0.0181 | −10,000,000*** |
| | | 25% | 0.0374 | 602,051*** | −0.0231 | −6,984,015*** |
| Distressed firms | AbCFO | 10% | 0.0925 | 18** | −0.0343 | −458*** |
| | | 25% | 0.0224 | 50 | −0.0423 | −209*** |
| | AbProdCost | 10% | −0.0273 | −2 | 0.0026 | 321*** |
| | | 25% | 0.0422 | 37 | −0.0263 | −205*** |
| | AbDiscEXP | 10% | 0.2546 | 9 | −0.0076 | −133 |
| | | 25% | 0.1258 | 20 | 0.0035 | 95 |
| | REM | 10% | 0.2582 | 13 | −0.0124 | −232*** |
| | | 25% | 0.0524 | 35* | −0.0109 | −135** |
| Non-distressed firms | AbCFO | 10% | 0.0430 | 93,973*** | −0.0374 | −10,320,000*** |
| | | 25% | 0.0364 | 635,859*** | −0.0576 | −7,399,179*** |
| | AbProdCost | 10% | 0.0102 | 48,229*** | −0.0001 | −384,489** |
| | | 25% | 0.0665 | 667,354*** | −0.0613 | −74,802,96*** |
| | AbDiscEXP | 10% | 0.0132 | 75,986*** | −0.0117 | −8,961,277*** |
| | | 25% | 0.0000 | 113,956*** | −0.0009 | −707,495*** |
| | REM | 10% | 0.0206 | 68,165*** | −0.0181 | −9,906,685*** |
| | | 25% | 0.0373 | 595,006*** | −0.0231 | −6,917,698*** |

Notes: Table 6 shows the differences in median Z-score and survival probability between unadjusted versus adjusted models. Dummy variable D equals 1 when the proxy measure for earnings-increasing manipulation of a firm-year observation exceeds the threshold level of 10% or 25% and equals 0 if otherwise. Panel A reports the percentage differences in Z-scores. Panel B reports the median Z-scores from the prediction model without adjustments for earnings management and is estimated by the logistic regression model of Eq. (4) for full sample, non-distressed firms, and distressed firms, respectively. The percentage difference in Z-scores is computed by subtracting adjusted Z-score from unadjusted Z-score and then deflated the difference by absolute adjusted Z-score. For the three different types of earning management (EM), we adopt abnormal operating cash flows (AbCFO), abnormal production costs (AbProdCost), and abnormal discretionary expenses (AbDiscEXP), which are estimated by the models proposed by Cohen et al. (2008) and Roychowdhury (2006), to measure real activities that may influence predictive power. REM, defined as (−1)AbCFO + AbProdCost + (−1)AbDiscExp, is an aggregate measure of real earnings management proposed by Cohen et al. (2008). SignRank is the statistics for sign rank test. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

includes a total of 4136 non-distressed firms and 27 distressed firms. The results suggest that the unadjusted Z-score model overestimates the survival probability for firms with aggressive real earnings management (D = 1) more than the adjusted model. By contrast, the values of the median difference in survival probabilities are all negative when firms engage in less real earnings

**Table 7**
Out-of-sample forecasts of financial distress.

| Sample | EM type | Threshold | D = 1 | | D = 0 | |
|---|---|---|---|---|---|---|
| | | | Median difference | SignRank | Median difference | SignRank |
| Panel A: Differences in survival probabilities between unadjusted and adjusted models | | | | | | |
| Full sample | AbCFO | 10% | 0.0320 | 16,621*** | −0.0467 | −2,094,390*** |
| | | 25% | 0.0298 | 128,493*** | −0.0624 | −1,454,037*** |
| | AbProdCost | 10% | 0.0249 | 12,558*** | −0.0084 | −1,629,263*** |
| | | 25% | 0.0711 | 133,081*** | −0.0522 | −1,395,975*** |
| | AbDiscEXP | 10% | 0.0320 | 19,393*** | −0.0209 | −1,801,748*** |
| | | 25% | 0.0289 | 91,774*** | −0.0280 | −864,388*** |
| | REM | 10% | 0.0384 | 19,316*** | −0.0269 | −1,920,802*** |
| | | 25% | 0.0453 | 119,421*** | −0.0326 | −1,227,569*** |
| Distressed firms | AbCFO | 10% | 0.1207 | 3 | −0.0818 | −79*** |
| | | 25% | 0.0132 | 6 | −0.1017 | −38*** |
| | AbProdCost | 10% | 0.0589 | 1 | −0.0130 | −68*** |
| | | 25% | 0.0785 | 14 | −0.0776 | −35*** |
| | AbDiscEXP | 10% | 0.4681 | 2 | −0.0275 | −66*** |
| | | 25% | 0.3544 | 4 | −0.0329 | −52** |
| | REM | 10% | 0.5366 | 4 | −0.0448 | −71*** |
| | | 25% | −0.0068 | −4 | −0.0450 | −43*** |
| Non-distressed firms | AbCFO | 10% | 0.0307 | 16,159*** | −0.0465 | −2,070,208*** |
| | | 25% | 0.0299 | 127,116*** | −0.0624 | −1,439,988*** |
| | AbProdCost | 10% | 0.0248 | 12,407*** | −0.0084 | −1,609,596*** |
| | | 25% | 0.0710 | 130,470*** | −0.0521 | −1,382,478*** |
| | AbDiscEXP | 10% | 0.0315 | 19,181*** | −0.0209 | −1,780,790*** |
| | | 25% | 0.0289 | 90,735*** | −0.0279 | −851,164*** |
| | REM | 10% | 0.0379 | 18,900*** | −0.0269 | −1,897,988*** |
| | | 25% | 0.0454 | 118,088*** | −0.0325 | −1,213,383*** |

| Sample | N | Performance (%) | Unadjusted Z-score model | EM type | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | AbCFO | | AbProdCost | | AbDiscEXP | | REM | |
| | | | | D10 | D25 | D10 | D25 | D10 | D25 | D10 | D25 |
| Panel B: Hit rates and Type I or II errors for distressed and non-distressed firms | | | | | | | | | | | |
| Distressed firms | 21 | Hit rate | 0.62 | 0.52 | 0.52 | 0.67 | 0.67 | 0.62 | 0.57 | 0.57 | 0.62 |
| | | Type I error | 0.38 | 0.48 | 0.48 | 0.33 | 0.33 | 0.38 | 0.43 | 0.43 | 0.38 |
| Non-distressed firms | 3253 | Hit rate | 0.79 | 0.87 | 0.86 | 0.80 | 0.81 | 0.82 | 0.80 | 0.83 | 0.81 |
| | | Type II error | 0.21 | 0.13 | 0.14 | 0.20 | 0.19 | 0.18 | 0.20 | 0.17 | 0.19 |

Notes: This table shows the results of differences in survival probabilities of out-of-sample forecasts of financial distress and hit rates for distressed and non-distressed firms. Panel A reports the differences in survival probabilities of out-of-sample forecasts of financial distress. Panel B reports the hit rates and Type I or II errors. Dummy variable D equals 1 when the proxy measure for earnings-increasing manipulation of a firm-year observation exceeds the threshold level of 10% or 25% and equals 0 if otherwise. For the three different types of earning management (EM), we adopt abnormal operating cash flows (AbCFO), abnormal production costs (AbProdCost), and abnormal discretionary expenses (AbDiscEXP), which are estimated by the models proposed by Cohen et al. (2008) and Roychowdhury (2006), to measure real activities that may influence predictive power. REM, defined as (−1)AbCFO + AbProdCost + (−1)AbDiscExp, is an aggregate measure of real earnings management proposed by Cohen et al. (2008). SignRank is the statistics for sign rank test. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

management (D = 0), suggesting that the unadjusted Z-score model underestimates the survival probability for firms with less real earnings management relative to the adjusted model.[5]

Panel B of Table 7 shows the hit rates and Type I or II errors for distressed and non-distressed firms in out-of-sample prediction. Incorporating real activity earnings management into the model yields mixed results with respect to distressed firms. Specifically, the effective adjustments, including incorporating AbProdCost into the model, help achieve a hit rate of 67%, which is greater than the hit rate of 62% for the unadjusted model. Moreover, the Type I error for the AbProdCost-adjusted model is 33%, whereas the error is 38% for the unadjusted model. By contrast, the adjusted model that incorporates AbCFO results in a hit rate of only 52%, which is substantially less than the hit rate of 62% of the unadjusted model.

The adjustments, however, unanimously achieve superior hit rates for non-distressed firms. For instance, the hit rates of the adjusted models range from 80% to 87%, which are greater than the rate of 79% for the unadjusted model. For Type II errors,

[5] We further retest our models with proxies for the extent of real earnings management by incorporating not only the dummy interaction terms but also the dummy intercept terms in Eq. (5). The untabulated results are quantitatively the same as the results in Table 5. Specifically, the unadjusted Z-score model overestimates (underestimates) the likelihood of financial distress compared to the adjusted model for firms with aggressive (less or no) real earnings management. In sum, the findings provide support for adjusting the prediction model.

using the results of REM as an example, the Type II error is less than 19%, whereas the Type II error for the unadjusted model is 21%.

### 5.3. Survival probability from accounting-based model adjusted for real earnings management deciles

We perform a sensitivity test to replace the dummy slopes in Eq. (5) with decile variables, and then we replicate the out-of-sample prediction procedure. The differences in survival probability between the unadjusted and adjusted model are shown in Fig. 2. The figure shows that the survival probabilities computed by the unadjusted model are underestimated for firms with less real earnings management from the first to the eighth deciles of all types of real earnings management, whereas the probabilities are overestimated for the firms located in the ninth and the tenth deciles. The convex curve, nevertheless, depicts a non-monotonic relationship between real earnings management and the difference in survival probability. The phenomenon is consistent with the notion that the firms in the first two deciles, which seemingly conduct the least earnings manipulation or even adopt income-decreasing schemes, may be firms that borrow heavily from the future to boost their earnings in previous years and thus encounter concurrent reversal of earnings management measures. Thus, firms in these two deciles may not be firms that are the least subject to earnings management.

Moreover, using the aggregate real earnings management, we are able to identify the greatest deviation from the survival probability of the adjusted model. Our findings indicate that taking into account real earnings management via dummy or ranking variables may result in as much as a 15% difference in predicted default probabilities.

## 6. Additional analyses

### 6.1. Test for discretionary accruals

This section adopts discretionary accruals as an alternative earnings management measure and conducts additional tests. In the previous sections, we incorporate real earnings management measures to enhance the effectiveness of the Z-score model. Firms may increase current period revenues or reduce discretionary expenditures with or without the intention to mislead financial report readers. Accordingly, in contrast to the test results with respect to real earnings management measures, the corresponding test results using discretionary accruals may or may not be consistent. Compared with real earnings management measures, significant discretionary accruals may more likely result from intentional misleading instead of non-strategic efforts to survive hardships exerted by distressed firms.

Following Kothari et al. (2005), we estimate accrual-based earnings management using the modified Jones method (Dechow et al., 1995) with consideration of operating performance. The regression models are as follows:

$$TA_{i,t} = \alpha_1\left(1/A_{i,t-1}\right) + \alpha_2\left(\frac{\Delta SALE_{i,t-1}}{A_{i,t-1}}\right) + \alpha_3\frac{PPE_{i,t-1}}{A_{i,t-1}} + \alpha_4 ROA_{i,t-1} + \varepsilon_{i,t}, \tag{6}$$

$$NDA_{i,t} = \hat{\alpha}_1\left(1/A_{i,t-1}\right) + \hat{\alpha}_2\left(\frac{\Delta SALE_{i,t} - \Delta REC_{i,t}}{A_{i,t-1}}\right) + \hat{\alpha}_3\frac{PPE_{i,t}}{A_{i,t-1}} + \hat{\alpha}_4 ROA_{i,t-1}, \tag{7}$$

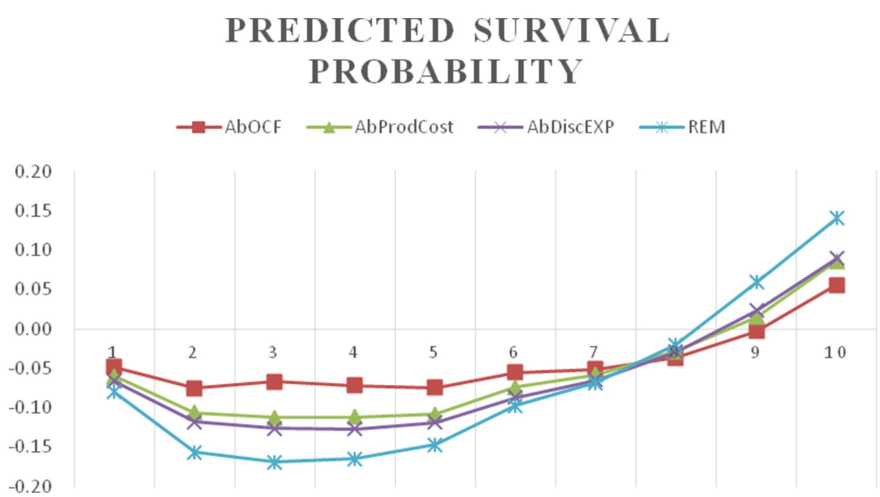


**Fig. 2.** Difference of predicted survival probability between the unadjusted model and adjusted model with real earnings management.

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005

where subscript $i$ denotes the company and subscript $t$ denotes the year; ΔREC is defined as the change in net receivables; PPE is defined as the gross property, plant, and equipment; and ROA is defined as return on assets. TA, the total accruals, is defined as

$$TA_{i,t} = \left(\Delta CA_{i,t} - \Delta CL_{i,t} - \Delta CASH_{i,t} + \Delta STD_{i,t} - DEP_{i,t}\right) / A_{i,t-1}, \tag{8}$$

where ΔCA is the change in current assets; ΔCL is the change in current liabilities; ΔCASH is the change in cash and cash equivalents; ΔSTD is the change in debt included in current liabilities; DEP represents depreciation and amortization expenses; and A represents total assets. We insert year $t-1$'s coefficient calculated in Eq. (6) into Eq. (7) for year $t$ to obtain the difference between TA and NDA of company $i$ during year $t$, which is defined as the discretionary accrual (DA). We let firms within the same industry share the same set of year $t$ regression estimates in Eq. (6) to control for time and industry effects.

**Table 8**
Additional test results with respect to discretionary accruals.

Panel A: Summary statistics for discretionary accruals

| Mean | Median | Min. | Q1 | Q3 | Max. | Std. dev. |
|---|---|---|---|---|---|---|
| 0.0034 | 0.0103 | −0.5059 | −0.0536 | 0.0658 | 0.6835 | 0.1154 |

Panel B: Differences in mean and median discretionary accruals between distressed and non-distressed firms

| Mean discretionary accruals | | | | Median discretionary accruals | | | |
|---|---|---|---|---|---|---|---|
| Distressed firm | Non-distressed firm | Diff. | $t$ | Distressed firm | Non-distressed firm | Diff. | $Z$ |
| 0.0214 | 0.0032 | 0.0181 | 1.15 | 0.0077 | 0.0103 | −0.0026 | −0.14 |

Panel C: Results of regression model adjusted for discretionary accruals

| Variable | Not controlled for year effect | | | | Controlled for year effect | | | |
|---|---|---|---|---|---|---|---|---|
| | Threshold | | | | Threshold | | | |
| | D10 | | D25 | | D10 | | D25 | |
| | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ |
| Intercept | 3.9196 | 131.15*** | 3.9821 | 135.79*** | 3.1912 | 9.49*** | 3.2492 | 9.86*** |
| ZWC | 0.3370 | 0.20 | 0.5921 | 0.52 | 0.2432 | 0.10 | 0.4512 | 0.30 |
| ZRE | 0.6060 | 2.57 | 0.3099 | 0.55 | 0.7547 | 3.78* | 0.4948 | 1.31 |
| ZEBIT | 5.8878 | 15.84*** | 6.6722 | 17.14*** | 5.7415 | 13.33*** | 6.4852 | 14.25*** |
| ZLEV | 0.2819 | 7.30*** | 0.2706 | 5.87** | 0.3299 | 8.65*** | 0.3212 | 7.22*** |
| ZATO | 1.1301 | 6.42** | 1.0911 | 5.07** | 1.2216 | 7.15*** | 1.1776 | 5.77** |
| DZWC | −0.0011 | 0.00 | −0.8482 | 0.39 | −0.0229 | 0.00 | −0.5912 | 0.20 |
| DZRE | −0.2412 | 0.09 | 0.5828 | 0.75 | −0.1766 | 0.06 | 0.5101 | 0.62 |
| DZEBIT | 1.1031 | 0.13 | −0.7142 | 0.07 | 0.3401 | 0.01 | −1.0988 | 0.16 |
| DZLEV | −0.2091 | 1.82 | −0.1070 | 0.52 | −0.2115 | 1.58 | −0.1189 | 0.61 |
| DZATO | 0.5651 | 0.24 | 0.1587 | 0.05 | 0.5722 | 0.23 | 0.1675 | 0.06 |
| R-square | 0.0177 | | 0.0176 | | 0.0189 | | 0.0189 | |

Panel D: Out-of-sample forecasts of financial distress — Differences in survival probabilities between unadjusted versus adjusted models

| Sample | Threshold | D = 1 | | D = 0 | |
|---|---|---|---|---|---|
| | | Median difference | SignRank | Median difference | SignRank |
| Full sample | 10% | −0.0166 | −15,788*** | 0.0007 | 224,870*** |
| | 25% | 0.0167 | 68,319*** | −0.0067 | −652,675*** |
| Distressed firms | 10% | −0.0485 | −1 | −0.0005 | −26 |
| | 25% | 0.0215 | 2 | −0.0177 | −33 |
| Non-distressed firms | 10% | −0.0163 | −15,649*** | 0.0007 | 226,670*** |
| | 25% | 0.0167 | 67,968*** | −0.0066 | −644,047*** |

Notes: This table shows the results of additional tests for models adjusted for accrual-based earnings management. Panel A reports the summary statistics, with Min., Q1, Q3, Max., and Std. Dev. Representing the minimum, first quartile, third quartile, maximum, and standard deviation, respectively, for discretionary accruals. Panel B reports the univariate analyses for differences between distressed and non-distressed firms. Panel C reports the multivariate analyses adopting the models adjusted for discretionary accruals estimated from Eq. (5). Panel D reports the differences in survival probabilities between unadjusted versus adjusted models. D10 and D25 represent the two different earnings management thresholds of 10% and 25%, respectively. ZWC is the ratio of working capital to total assets. ZRE is the ratio of retained earnings to total assets. ZEBIT is the ratio of earnings before interest and taxes to total assets. ZLEV is the ratio of market value of equity to book value of liabilities. ZATO is the ratio of sales revenue to total assets. The explanatory variables with the names that start with D represent the product of the earnings management dummy variable and the respective five Altman Z-score factors. For instance, DZWC = D × ZWC, where D equals 1 when the proxy variable for earnings management during the firm-year lies within the top 10% or top 25% and 0 otherwise. We present t- and Z-statistics for tests of differences (Diff.) in mean and median discretionary accruals, respectively. SignRank is the statistics for sign rank test. $\chi^2$ is the chi-square statistic for estimated coefficient, Est. coeff., in logistic regression. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

For all tests, we replace real earnings management measures with accrual-based earnings management measures and report the results in Table 8. Panel A shows that both mean and median discretionary accruals are approximately zero, consistent with the theoretical value. Panel B shows that distressed firms, on average, have a non-significantly greater DA than non-distressed firms for both mean and median values. Panel C shows that factors ZEBIT, ZLEV, and ZATO exhibit significant predictive power for financial difficulties. However, the coefficients of the interaction between the earnings management dummy and the three factors do not appear to be significant. In sum, accrual-based earnings management measures fail to help explain the weights of the five Z-score factors on financial distress, whether or not the year effects are incorporated.

To build Panel D of Table 8, we redo the tests in Table 7 by replacing real earnings management measures with discretionary accruals. Panel D shows the results for out-of-sample prediction of financial distress by incorporating the accrual-based measures. Adopting a 25% threshold to identify aggressive accrual-based earnings management, we document an overestimation for survival probabilities using an unadjusted Z-score model for high-DA firms and an underestimation for low-DA firms. However, we obtain the opposite results when we adopt the 10% threshold instead. These mixed results are observed regardless of how the sample is partitioned.

In sum, we obtain mixed evidence on whether incorporating DA to form the interaction variables improves the predictive power of the distress prediction Z model. Specifically, in spite of our finding that the Z-score model may be contaminated because potentially distressed firms boost revenues or reduce expenditures on rainy days, the sensitivity test results show that the exceptionally high accruals of these firms do not appear to mislead the credit risk raters using the conventional set of accounting measures.

### 6.2. Adopting Ohlson's model to predict financial distress

This section replaces the Z-score model with Ohlson's (1980) O-score model and reconducts our analyses in response to Begley et al. (1996)and Grice and Ingram (2001), who document that Altman's model does not perform effectively in the recent period. Ohlson includes nine determinants to predict financial distress. The common set of accounting predictors includes leverage ratio (TLTA), working capital to total assets (WCTA), and net income to total assets (NITA). Ohlson, nevertheless, adds size (Size),[6] current liabilities divided by current assets (CLCA), a dummy variable representing total liabilities exceeding total assets (OENEG), funds provided by operations divided by total liabilities (FULT), a dummy variable of the losses in the two previous years (INTWO), and change in net income (CHIN) in his O-score model. We reexamine the O-score model and the adjusted O-score model that takes into account real earnings management and document significantly superior predictive power with respect to the latter setting. The empirical results are reported in Table 9.

Panel A of Table 9 reports the summary statistics of the explanatory variable of the O-score model. The minimums of WCTA, NITA, FUTL, and CHIN are negative, suggesting that certain firms experience losses and run out of funds. Panel B reports the regression results of tests incorporating proxies for the aggregate measure of real activity earnings management. In general, incorporating proxies for real earnings management enhances the explanatory power of the predictors adopted by the O-score model. For example, including REM significantly enhances the explanatory powers of Size, TLTA, and OENEG when predicting firms' survival probability. Panel C reports the differences in median survival probability between the conventional O-score model and the adjusted model with an aggregate measure of real earnings management. The positive coefficients for firms with aggressive real earnings management ($D = 1$) suggest that the O-score model overestimates the survival probability for these firms. The negative coefficient for firms with less or no real earnings management ($D = 0$) suggests that the O-score model underestimates the survival probability for firms engaging in less or no real earnings management. In sum, the tests regarding the O-score model yield similar findings that take into account real earnings management, which enhances the accuracy of financial distress prediction.

### 6.3. Impact of global financial crisis

We further examine whether the global financial crisis (GFC) affects the performance of our adjusted default prediction models. We divide our sample into pre- and post-GFC subsamples, which consist of the observations before 2007 and those after 2010, respectively, retesting the unadjusted and adjusted models. The untabulated results support the notion that partitioning the observations by the extent to which firms are subject to earnings management may improve the effectiveness of predicting financial distress.[7]

## 7. Conclusion

This study conjectures that taking into account potential financial report manipulation enhances the default predictability of accounting-based scoring models. We use Chinese exchange-listed firms as our sample to examine the extent to which the potential manipulative conducts, including excessive reduction of expenses and acceleration of sales recognition, influence the effectiveness of the model in assessing the likelihood of financial distress. We find that compared with the adjusted model, which incorporates the effects of real earnings management, both the Z-score and survival probability derived from the Altman's

[6] Ohlson (1980) adopts the GNP price-level index in 1968 as a base to scale firm size. This study, by contrast, adopts the GNP price-level index in 1978 as a base to cope with the inflation during the 1970s.

[7] We appreciate the suggestion of an anonymous referee that we should consider the impact of the global financial crisis in our analyses.

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005

**Table 9**
Sensitivity test: Results for adjusted O-score model.

Panel A: Summary statistics for O-score variables

| Variable | Mean | Median | Min | Q1 | Q3 | Max | Std. dev. |
|---|---|---|---|---|---|---|---|
| Size | 28.0738 | 27.9985 | 25.3962 | 27.3766 | 28.6800 | 32.8052 | 1.04 |
| TLTA | 0.5197 | 0.5124 | 0.0424 | 0.3804 | 0.6347 | 2.6688 | 0.23 |
| WCTA | 0.0662 | 0.0749 | −1.5129 | −0.0720 | 0.2223 | 0.7452 | 0.24 |
| CLCA | 1.0155 | 0.8547 | 0.0431 | 0.6118 | 1.1928 | 5.4921 | 0.71 |
| NITA | 0.0206 | 0.0278 | −1.2050 | 0.0083 | 0.0538 | 0.2716 | 0.08 |
| FUTL | 0.0979 | 0.0594 | −1.0435 | 0.0131 | 0.1477 | 1.6219 | 0.23 |
| INTWO | 0.0458 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 | 0.21 |
| OENEG | 0.0179 | 0.0000 | 0.0000 | 0.0000 | 0.0000 | 1.0000 | 0.13 |
| CHIN | 0.0204 | 0.0528 | −1.0000 | −0.2013 | 0.2591 | 1.0000 | 0.52 |

Panel B: Regression results with adjustments for real earnings management — REM

| Variable | Not controlled for year effect | | | | Controlled for year effect | | | |
|---|---|---|---|---|---|---|---|---|
| | Threshold | | | | Threshold | | | |
| | D10 | | D25 | | D10 | | D25 | |
| | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ | Est. coeff. | $\chi^2$ |
| Intercept | 5.0421 | 1.07 | 5.2540 | 0.90 | 3.9912 | 0.61 | 4.3659 | 0.58 |
| Size | 0.0226 | 0.02 | 0.0248 | 0.02 | 0.0299 | 0.03 | 0.0308 | 0.03 |
| TLTA | −0.4308 | 0.42 | −0.2835 | 0.16 | −0.7344 | 1.06 | −0.5580 | 0.54 |
| WCTA | −0.3178 | 0.08 | −1.3105 | 1.19 | −0.0078 | 0.00 | −1.2339 | 0.98 |
| CLCA | −0.1320 | 0.20 | −0.3862 | 1.67 | −0.0504 | 0.03 | −0.3556 | 1.37 |
| NITA | 2.3783 | 3.49* | 2.8035 | 4.41** | 1.8814 | 1.92 | 2.3987 | 2.78* |
| FUTL | 2.3980 | 4.74** | 2.2469 | 3.81* | 2.5399 | 5.10** | 2.3922 | 4.18** |
| INTWO | 0.1047 | 0.04 | 0.0536 | 0.01 | −0.0364 | 0.00 | −0.0154 | 0.00 |
| OENEG | −1.5516 | 4.26** | −1.8522 | 5.18** | −1.2756 | 2.69 | −1.6506 | 3.88** |
| CHIN | 0.1016 | 0.11 | 0.1473 | 0.17 | 0.0851 | 0.07 | 0.1467 | 0.17 |
| DSize | 0.3381 | 0.68 | 0.2776 | 0.73 | 0.3993 | 0.93 | 0.2822 | 0.76 |
| DTLTA | −8.1696 | 5.15** | −2.5424 | 2.66 | −8.5218 | 5.61** | −2.2197 | 1.98 |
| DWCTA | 1.5998 | 0.18 | 5.0373 | 5.03** | 1.5638 | 0.16 | 5.1131 | 5.00** |
| DCLCA | −0.1150 | 0.02 | 0.6496 | 1.27 | −0.2924 | 0.09 | 0.6440 | 1.19 |
| DNITA | 1.1588 | 0.02 | −5.2473 | 1.39 | 0.7220 | 0.01 | −4.8195 | 1.14 |
| DFUTL | −6.0108 | 1.28 | −1.0150 | 0.08 | −6.7099 | 1.74 | −1.3221 | 0.14 |
| DINTWO | 0.0469 | 0.00 | 0.0233 | 0.00 | 0.1294 | 0.00 | −0.0365 | 0.00 |
| DOENEG | 8.5607 | 7.83*** | 4.7671 | 7.09*** | 9.0626 | 8.30*** | 4.4725 | 6.05** |
| DCHIN | 1.2136 | 1.55 | 0.8181 | 1.63 | 1.2996 | 1.75 | 0.8388 | 1.70 |
| D | −3.9386 | 0.12 | −7.0797 | 0.61 | −5.1122 | 0.20 | −7.3374 | 0.66 |
| R-square | 0.0192 | | 0.0181 | | 0.0202 | | 0.0186 | |

Panel C: Differences in median survival probability between unadjusted versus adjusted models — REM

| Threshold | D = 1 | | D = 0 | |
|---|---|---|---|---|
| | Median difference | SignRank | Median difference | SignRank |
| 10% | 0.0124 | 135,412*** | −0.0002 | −1,694,749*** |
| 25% | 0.0035 | 421,531*** | −0.0005 | −1,217,012*** |

Notes: This table shows the results of robustness tests for adopting Ohlson's (1980) O-score model to predict financial distress. The sample includes 7362 observations. Panel A reports the summary statistics for O-score variables, with Min., Q1, Q3, Max., and Std. Dev. representing the minimum, first quartile, third quartile, maximum, and standard deviation, respectively. Panel B reports the regression results with adjustments for real earnings management. Panel C reports the differences in median survival probability between unadjusted versus adjusted models. Size is the natural logarithm of total assets scaled by GNP price-level index. The index assumes a base value of 100 for 1978. The index year is as of the year prior to the year of the balance sheet date. TLTA is total liabilities divided by total assets. WCTA is working capital divided by total assets. CLCA is current liabilities divided by current assets. OENEG is equal to 1 if total liabilities exceed total assets and 0 otherwise. NITA is net income, NI, divided by total assets. FUTL is funds provided by operations divided by total liabilities. INTWO is equal to 1 if net income was negative for the last two years and 0 otherwise. CHIN is change in net income, computed as $(NI_t - NI_{t-1}) / (|NI_t| + |NI_{t-1}|)$, where $NI_t$ is net income for the most recent period. REM, defined as (−1)AbCFO + AbProdCost + (−1)AbDiscExp, is an aggregate measure of real earnings management proposed by Cohen et al. (2008). AbCFO is abnormal operating cash flows. AbProdCost is abnormal production costs. AbDiscEXP is abnormal discretionary expenses. D10 and D25 represent the two different earnings management thresholds of 10% and 25%, respectively. The explanatory variables with the names that start with D represent the product of the earnings management dummy variable and the respective Ohlson's O-score factors. For instance, DSize = D × Size, where D equals 1 when the proxy variable for earnings management during the firm-year lies within the top 10% or top 25% and 0 otherwise. SignRank is the statistics for sign rank test. $\chi^2$ is the chi-square statistic for estimated coefficient, Est. coeff., in logistic regression. ***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.

model are overestimated for firms aggressively boosting the earnings, supporting our conjectures. We further find that both the Z-score and survival probability of the Altman's model are underestimated for firms subject to less or no earnings management.

The out-of-sample predictions, in general, suggest that incorporating factors regarding earnings management in the scoring mechanism yields a well-specified model and enhanced predictive power with unanimously greater accuracy in identifying

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005

non-distressed firms. Specifically, firms' real transactions prior to bankruptcy affect line items in their financial statements, especially retained earnings and earnings before interests and tax expenses, the two reported earnings-related Z-score factors. Consequently, if a researcher fails to consider the effect of earnings management, she may underestimate the probability of financial distress of firms engaging in aggressive earnings management and overestimate the probability of financial distress of firms engaging in less or no earnings management. Our results provide evidence of a fairly pronounced need to adjust accounting-based default prediction models. We suggest that succeeding studies should control the potential distortion from earnings management in the financial statements when assessing financial distress. Moreover, the practitioners may benefit from the sophisticated default prediction model, which is adjusted by earnings management to more accurately predict defaults.

Our study is, however, subject to certain limitations. First, the information content for each line item in the financial statements may vary across different countries because of their different business customs and laws. Therefore, our results may not imply that incorporating all types of earnings management results in a more accurate prediction of financial distress for other countries. Second, transactions reported in the off balance sheet are not captured to adjust the Z-score and survival probability even though we adjust real activity earnings management in the accounting-based prediction models.

## Acknowledgments

The authors gratefully acknowledge the financial support of the Ministry of Science and Technology (104-2410-H-155-010; 104-2410-H-155-011-), Yuan Ze University, and Tunghai University. We also receive insightful comments provided by Robert Durand, Bharat Sarath, Monica Tan, P. Joakim Westerholm, Rui Zhong, and the participants of the seminar in National Chiao Tung University, the 2014 International Conference on Corporate Finance and Capital Market in China, and the 2015 Financial Markets and Corporate Governance (FMCC) Conference in Western Australia. We especially appreciate the helpful suggestions provided by Balasingham Balachandran (Guest Editor) and an anonymous referee. All errors are our own.

## References

Altman, E.I., 1968. Financial ratios, discriminant analysis and the prediction of corporate bankruptcy. J. Financ. 23, 589–609.
Altman, E.I., Sabato, G., 2007. Modelling credit risk for SMEs: evidence from the U.S. market. Abacus 43, 332–357.
Altman, E.I., Haldeman, R.G., Narayanan, P., 1977. ZETA-analysis: a new model to identify bankruptcy risk of corporations. J. Bank. Financ. 1, 29–54.
Altman, E.I., Hartzell, J., Peck, M., 1995. A scoring system for emerging market corporate debt. Salomon Brothers 15 (May).
Aziz, A., Emanuel, D.C., Lawson, G.H., 1988. Bankruptcy prediction—an investigation of cash flow based models. J. Manag. Stud. 25, 419–437.
Beaver, W., 1967. Financial ratios as predictors of failure. J. Account. Res. 4 (Supplement), 71–111.
Becchetti, L., Sierra, J., 2002. Bankruptcy risk and productive efficiency in manufacturing firms. J. Bank. Financ. 26, 2099–2120.
Begley, J., Ming, J., Watts, S., 1996. Bankruptcy classification errors in the 1980s: an empirical analysis of Altman and Ohlson's models. Rev. Acc. Stud. 1, 267–284.
Blum, M., 1974. Failing company discriminant analysis. J. Account. Res. 12, 1–25.
Cohen, D., Zarowin, P., 2010. Accrual-based and real earnings management activities around seasoned equity offerings. J. Account. Econ. 50, 2–19.
Cohen, D., Dey, A., Lys, T., 2008. Real and accrual based earnings management in the pre and post Sarbanes Oxley periods. Account. Rev. 83, 757–787.
Deakin, E., 1972. A discriminant analysis of predictors of business failure. J. Account. Res. 10, 167–179.
Dechow, P.M., Sloan, R.G., Sweeney, A.P., 1995. Detecting earnings management. Account. Rev. 70, 193–225.
Edmister, R., 1972. An empirical test of financial ratio analysis for small business failure prediction. J. Financ. Quant. Anal. 7, 1477–1493.
Eisenbeis, R., 1977. Pitfalls in the application of discriminant analysis in business, finance, and economics. J. Financ. 32, 875–900.
Gentry, J.A., Newbold, P., Whitford, D.T., 1985. Classifying bankrupt firms with funds flow components. J. Account. Res. 23, 146–160.
Gombola, M., Haskins, M., Ketz, J., Williams, D., 1987. Cash flow in bankruptcy prediction. Financ. Manag. 16, 55–65.
Graham, J.R., Harvey, C.R., Rajgopal, S., 2005. The economic implications of corporate financial reporting. J. Account. Econ. 40, 3–73.
Grice, J., Ingram, R., 2001. Tests of the generalizability of Altman's bankruptcy prediction model. J. Bus. Res. 54, 53–61.
Gunny, K., 2010. The relation between earnings management using real activities manipulation and future performance: evidence from meeting earnings benchmarks. Contemp. Account. Res. 27, 855–888.
Keasey, K., Watson, R., 1987. Non-financial symptoms and the prediction of small company failure: a test of Argenti's hypotheses. J. Bus. Financ. Account. 14, 335–354.
Kothari, S.P., Leone, A.J., Wasley, C.E., 2005. Performance matched discretionary accrual measures. J. Account. Econ. 39, 163–197.
Lussier, R.N., 1995. A non-financial business success versus failure prediction model for young firms. J. Small Bus. Manag. 33, 8–20.
Merton, R.C., 1974. On the pricing of corporate debt: the risk structure of interest rates. J. Financ. 29, 449–470.
Micha, B., 1984. Analysis of business failures in France. J. Bank. Financ. 8, 281–291.
Mossman, C.E., Bell, G.G., Swartz, L.M., Turtle, H., 1998. An empirical comparison of bankruptcy models. Financ. Rev. 33, 35–54.
Ohlson, J., 1980. Financial ratios and the probabilistic prediction of bankruptcy. J. Account. Res. 18 (1), 109–131.
Ooghe, H., Joos, P., De Bourdeaudhuij, C., 1995. Financial distress models in Belgium: the results of a decade of empirical research. Int. J. Account. 30, 245–274.
Piesse, J., Wood, D., 1992. Issues in assessing MDA models of corporate failure: a research note. Br. Account. Rev. 24, 33–42.
Platt, H.D., Platt, M.B., 1990. Development of a class of stable predictive variables: the case of bankruptcy prediction. J. Bus. Financ. Account. 17, 31–51.
Roychowdhury, S., 2006. Earnings management through real activities manipulation. J. Account. Econ. 42, 335–370.
Taffler, R.J., Tisshaw, H., 1977. Going, going, gone—four factors which predict. Accountancy 88 (1083), 50–54.
Zavgren, C., 1983. The prediction of corporate failure: the state of the art. J. Account. Lit. 2, 1–38.

Please cite this article as: Lin, H.-W.W., et al., Modeling default prediction with earnings management, Pacific-Basin Finance Journal (2016), http://dx.doi.org/10.1016/j.pacfin.2016.01.005