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The Role of Earnings Management in Theoretical Development and Improving the Efficiency of Accounting-Based Financial Distress Prediction Models

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ABSTRACT

Examining the theoretical foundations of earnings management shows that companies have stronger incentive to use earnings management at the pre-bankruptcy stage. Consequently, accounting-based determinants retrieved from financial statements may be biased factors for financial distress. In this paper, we investigate whether taking into account real earnings management improves the specification of accounting-based financial distress prediction models. We test whether the inclusion of such attributes in financial distress prediction models improves their predictive ability. We use a sample of listed manufacturing companies in the Iran Stock Exchange during 2008 - 2017. Our findings suggest that the inclusion of earnings management significantly increases the predictive ability of accounting-based financial distress prediction models. Our results show that the real earnings management can provide predictive signals concerning financial distress and that an abnormal cash flow which proxies for real earnings management can play a relevant role in early warnings of financial distress. These results are of interest to market participants, auditors, regulating authorities, banks and other financial institutions that are interested in financial distress assessment.

1 Introduction

Corporate financial distress is one of the critical issues in corporate finance and it refers to the financial health of the companies. Bondholders become anxious regarding the reliability of corporations to which they are going to lend their money. So, default and credit rate of corporations are of primary importance to them while trying to invest their money in those companies [52]. Wruck [57] defines that a company is in financial distress when its cash flow is insufficient to cover its current obligations. The chances of causing financial distress increases when a firm's fixed costs are high, assets are illiquid, or revenues that are too sensitive to economic recessions. A company that is in financial distress can experience costs linked to the situation, such as more exclusive financing, opportunity costs of projects and less dynamic employees. The cost of borrowing additional capital of the firm will generally increase, increasing the much-desired funds to make it extra challenging and costly.

To fulfill short-term obligations, management might run longer-term profitable projects. The employees of a financially distressed firm usually have lower confidence and higher stress because of increasing the chance of bankruptcy, for which they will be out of their jobs. Under such a burden, workers can be less productive [35, 36, 37]. Moreover, financial distress may inflict negative shocks for each of the stakeholders and, therefore, the total (economic and social) cost of business failure may be large.

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financial distress generates various types of costs, not only for the direct (internal) stakeholders of the company – the entrepreneur, management and employees – but also for the direct environment of the firm – shareholders, equity and credit suppliers, clients and suppliers, the Government – and the economy as a whole. In his way, company failure may have important consequences with respect to the employment and the (regional) economic welfare [53]. Consequently, the prediction of company failure is important not only from the 'individual' point of view but also for the 'society' as a whole [6]. As well as, financial distressed may bring a bad reputation for the company because investors would see the company as an incompetent firm.

Due to this, the company may face a disaster whereby will experience a dramatic drop in its market value of equity as investors will shun away from buying the company's share and if there is no action are taken, the ownership of the company itself as its weak condition calls out potential buyers to place their names on the company. In view of the above discussion, predicting financial distress is a very powerful tool that can help both corporations and investors in making wise and prudent decisions. It helps managers to take preventive actions in order to save the firm from falling prey to distress. They can improve the situation and try to find solutions before the condition gets worse. With the ability to predict the probability of financial distress, investors can improve their investment decisions and the loss by removing their money from distress-prone companies. One of the most common and accepted methods for examining corporate performance is financial ratio analysis. Over the years, financial ratios have been applied and its accuracy has been proven to determine the financial status of a firm. It has also been used to predict financial distress or bankruptcy by market participants.

Due to its ease of application and understanding, today, investors and financial analysts still use accounting-based models in their decision making. Accounting models thus dominate the world of financial distress prediction. The quality of accounting information is crucial for these models because they suppose that this information gives a fair and reliable representation of firm activity. This is why accounting regulatory organizations have decided to issue standards that firms should follow when presenting their financial statements so that they reflect their economic situation as closely as possible and the performance they achieve over time. However, the rules that are used to present financial accounts allow a certain degree of flexibility and make it possible for managers to use their judgment to publish accounting figures that reflect their discretionary objectives [22, 56]. For example, the punishment effect on the behavior of managers, which may encourage them to make decisions to prevent bankruptcy [4]. As a consequence, the way accounts are presented, and the information they convey, can be modified and even distorted depending on the nature of the goals that managers have decided to pursue [22, 31]. Even if such manipulations are legal, because they are regulated, the fact remains that they may lead to distortions that might be detrimental to financial distress models. Although it is known that some firms, and especially firms experiencing financial issues, manipulate their earnings to voluntarily change the image conveyed by their accounts [11, 21, 27, 47], but no one has tried to analyze whether this rather special information could improve model accuracy. This is the reason why in this studied this question.

To do so, we compared the results achieved using an initial model that is solely based on accounting data with results of the adjusted model with a variable that is intended to represent real activity manipulations. Our findings can help today's knowledge in the growing domain of earnings management and will expand the evidence available to predict financial distress and ultimately bankruptcy. Furthermore, the findings are useful and it provides empirical evidence to credit providers, suppliers, customers, investors, auditors and even regulators about the importance and the effect of earning management.

2 Literature Review

2.1 Traditional Financial Distress Prediction Models

Early financial distress studies developed different forms of prediction models based on cash flow or accrual-based financial ratios. Empirical financial distress prediction models have been developed in three major stages [36, 49], from the estimation techniques that use only one dependent measure, such as univariate analysis, to the statistical techniques which analysis variables in one or multiple relationships, such as multiple discriminant analysis, logistic and prohibit analysis, to the more complicated computerized analysis, such as recursive partitioning, hazard models, artificial neural network. Initial financial distress prediction models have used financial ratios to predict the financial health of the firms.

These financial ratios are easy to access due to their availability in the financial statements of the firms, which are commonly available to the public [55]. Using financial ratios on predicting financial distress date back to the 1930s with the analysis of indicators for forecasting bankruptcy starting with the study from Fitzpatrick [24]. In the 1960s, Beaver, using statistical techniques, introduced the first model of predicting financial distress using financial ratios. He defined financial distress as default on interest payments on its debt, overdraw its bank account, declares bankruptcy or unable to pay preferred stock dividends. Thirty indices were constructed based on financial statements and from profile analysis, it was concluded that bankrupt companies' indices deteriorated much more quickly than those of companies that remained healthy. In his conclusion, he suggested that subsequent studies should use various indicators simultaneously in constructing the models, which would ultimately determine the tendency of subsequent papers with regards to forecasting distress [44].

Altman [2] highlighted the advantages of multiple discriminant analysis (MDA) over the univariate analysis technique is that: MDA is a statistical technique used to classify an observation into one of several a priori grouping dependent upon the observation's individual characteristics. It is used primarily to classify and/or make predictions in problems where the dependent variable appears in qualitative form, for example, male or female, bankrupt or non-bankrupt. The MDA techniques have the advantage of considering an entire profile of characteristics common to relevant firms, as well as the interaction of these properties. A univariate study, on the other hand, can only consider the measurement used for group assignments one at a time [2]. Given the above advantages, MDA has been used by many researchers in developing their business failure prediction models. MDA has some weaknesses. First, MDA requires that the classifications between the fail and the non-fail companies are linearly separated, so that the discriminant scores above or below the cutoff point represent healthy or unhealthy companies. But most variables do not have such linear relationships. Second, multivariate normality is often violated [7, 17, 48] and may cause bias in the estimated error rates because the ratio's signal cannot vacillate to another ratio or set of ratios [14].

Minussi et al. [43] stated that the advantage of logistic regression compared with MDA lies in its coverage of possibilities, given that it is not necessary to guarantee neither the normality of residues nor the existence of homogeneity of the variance. Moreover, the logistic regression models enable the likelihood of a company going into bankruptcy to be estimated [44, 6]. An alternative approach for accounting-based models draws from contingent claims. The contingent claims approach is based on market information. In an implementation, market-based models follow the definition that a firm is a distress if the value of total assets is lower than the value of liabilities. The set-up of market-based models is given by the option pricing approach of Black and Scholes and the derivative pricing model of Merton (BSM) [8]. Market-based models regard firm equity as a call option on the value of the firm's assets with a strike price that equals the face value of liabilities. The firm is distress when the call option expires worthless. It follows that the probability of bankruptcy is the probability of a worthless option i.e. that the value of assets is less than the face value of liabilities at the end of the holding period [8]. The accounting-based financial distress prediction models differ from the Market-based models primarily in the critical factor adopted to predict firm financial distress. Unlike Market-based models, 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 [41]. Therefore, the model used in this study adjusts for the effect of earnings management in the accounting-based models, instead of using a Market-based models approach.

2.2 Earnings Management

The first study regarding earnings management topic has its origin in the middle of the twentieth century when Hepworth [32] analyzed the smoothing on incomes. Nonetheless, the cornerstone definition of earnings management was not established until the late nineties, when Healy and Wahlen [31] defined it as “earnings management occurs when managers use judgment in financial reporting and in structuring transactions to alter financial reports to either mislead some stakeholders about the underlying economic performance of the company or to influence contractual outcomes that depend on reported accounting numbers”.

This definition then refers to the alteration of financial statements so that managers can hide information in order not to be transparent and mislead shareholders and/or outsiders. The definition provided by these authors has become a cornerstone on the topic and then, earnings management is defined as the intended manipulation of financial statements. In this line, every author has developed novel definitions according to their study purpose but, based on this manipulation notion. For example; Garcia-Lara et al. [25] established earnings management as “intentionally conducted management practices in order to report the desired results and not the real ones”, while Scott [49] determined it as “the choice of accounting actions that can affect earnings with the purpose of obtaining its desired objective”. Thus, earnings management describes an activity carried out by managers to alter financial statements to achieve their purposes, suggesting that this term is a financial reporting phenomenon [55]. A review of the earnings management literature shows that management has two main tools available to conduct earnings management. The first type, accounting earnings management, refers to “the interpretation of accounting standards and their application to transactions and events that has already occurred” [23]. Examples of accounting earnings management include the selection of accounting methods such as the depreciation or pricing of inventory. The second type, real earnings management, is defined:

[. . .] as departures from normal operational practices, motivated by managers’ desire to mislead at least some stakeholders into believing that certain financial reporting goals have been met in the normal course of operations [4, 45].

Manipulation of real activities is done to boost earnings through sales manipulation, discretionary expenses reduction, or overproduction [48]. 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 (CGS) 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 [41]. Gunny [26] finds that real earnings management has a significantly negative effect on future performance. Tabassum et al. [50] document evidence that firms engaged in real earnings management through abnormal production costs face lower financial performance in subsequent years. Numerous studies document that REM is employed in various contexts. As discussed previously, financial distress models can be broadly classified into two categories: accounting-based and price-based. Since previous studies have shown that EM influences the informativeness of financial information in equity markets, in the context of my setting it is likely to influence the predictive power of accounting-based predictors used in various prediction models. Given that EM measures are more directly associated with the informativeness of earnings, this study focuses on the real earnings management measures.

2.3 Hypothesis Development

It is argued that firms are engaged in earnings management because they fail to achieve the earnings benchmark [28]. In the earnings management literature, one would intuitively expect to see upward earnings behavior from highly distressed firms, as it appears that this technique makes it possible to improve a firm's financial situation, particularly when it is close to failure [16, 47]. This can be explained in two ways. Managers can be incentivized to report high earnings so as to avoid debt covenant violations and probable bankruptcy [18]. In such cases, managers are primarily concerned with the short-term survival of their firm.

For instance, DeFond and Jiambalvo [20] show positive unexpected earnings in the year prior to default, consistent with managers manipulating earnings to prevent default [18]. Managers of financially distressed firms may also manipulate earnings upwards out of self-interest for various reasons [26]. They may seek to manipulate information to keep their job or to highlight firm performance and consequently reap the benefits in the form of bonuses [22]. In fact, Bergstresser and Philippon [11] show that managers who have the strongest incentives are more likely to make use of earnings management. Jensen and Meckling [34] claimed that financially distressed firms face serious agency problems between managers and external capital providers due to asymmetric information. Information asymmetry between managers and external capital providers allows managers of financially distressed firms to employ various approaches to minimize the negative effect of financial distress.

Rogers and Stocken [46] document that managers of financially distressed firms are more likely to disclose optimistic forward-looking information to mitigate the potential negative responses from the markets. Lee [37] finds that financial distress is one of the incentives for firms to inflate reported cash flow from operations. Overall, these studies demonstrate that financially distressed firms are motivated to use aggressive earnings management and forecasting techniques to mitigate the potential negative impact of financial distress [33]. Therefore, it is possible that firms involved in earnings management intend to report higher income through higher sales revenue. By giving discounts on the selling price, the firm accelerates the sales volume in the current year, which causes the earnings for the current year to increase [48]. Apart from managing cash flow from operations, Roychowdhury [48] and Gunny [29] classify manipulating production costs as another form of real earnings management activity. Production costs are measured as the sum of the cost of goods sold (CGS) and the change in inventory. In managing the production costs, the firm increases the volume of production more than normal levels. This activity causes production costs to increase but the fixed cost per item reduces because it is spread to the larger volume of productions.

Consequently, the CGS per unit decreases and profit margin per sale item increases [42, 53]. However, overproduction will lead to higher total production costs than normal production costs for a given level of sales. By doing this, firms succeed in improving their profit margins but at the same time incur production costs to be abnormally high. Discretionary expenses manipulation is another type of real earnings management through which managers can manage earnings. According to Graham et al. [28] managers prefer earnings management using manipulation activities including reduction of discretionary expenses. Lee & Swenson [40], citing Bushee [12] show that managers tend to reduce research and development expenditures to hit their earnings targets. Baber et al. [40] find that relative R&D spending is correlated with managers' incentives to report positive or increasing income in the current period [40]. Gunny [30] finds that real earnings management negatively affects subsequent operating performance in terms of low future earnings and cash flows. Bazrafshan [9] examined the earnings behavior of bankrupt companies in the Tehran Stock Exchange. Their findings show that bankrupt companies make profit management in the pre-bankruptcy year, either by accruals manipulating or by real activities.

Therefore, the literature reiterates the existence of accounting number manipulation. All financial distress prediction models that are designed with accounting variables rely on the assumption that financial statements are reliable and that they offer a true and fair view of a firm's financial situation. However, the reality is rather different. Indeed, firms may manage their accounting statements to artificially improve their situation and hence distort their true financial picture. Consequently, one may reasonably assume that such practices may somehow alter the accuracy of financial distress prediction models. We investigate whether real earnings management for operation, production, and expenditures activities affect the specification of the adjusted accounting-based financial distress prediction model. It is argued that the information content of financial reporting may be greater and more precise after controlling real transactions for earnings management, and the adjusted accounting-based financial distress prediction model may be more efficient in detecting firms' financial distress. Hence, the following hypotheses established:

H1: The accounting-based financial distress prediction model has more predictive power after incorporating abnormal cash flows from operating activities, which proxies for real earnings management.

H2: The accounting-based financial distress prediction model has more predictive power after incorporating abnormal production costs, which proxies for real earnings management.

H3: The accounting-based financial distress prediction model has more predictive power after incorporating abnormal discretionary expenditure, which proxies for real earnings management.

3 Research Design

3.1 Data and Sample Selection

Our empirical analysis use data, which is downloaded from Tehran's Stock Exchanges (TSE) Database. To create the sample, we downloaded the financial statement data all listed manufacturing firms in TSE from 2007 to 2016 for Iranian firms, which are available on the Comprehensive Database of All Listed Companies (Codal) database. For 2007 to 2016 accuracy tests, accounting data has been retrieved from 2006 to 2016 to compute the financial ratios by using accounting measures at the beginning of each fiscal year. The Codal specifically provides information about the reasons for a firm's delisting, which we used to identify financially distressed firms. Financially distressed firms are firms that including article 141 of the Iranian's Trade Law.

According to article 141 of the Iranian's Trade Law Amendment provides that "if in effect entered losses at least half the firm's capital destroys, the board of directors shall immediately invite the extraordinary general meeting of shareholders to decision making the Liquidation or survival of the company". Considering the conditions, 348 firm-year observations have been identified as financially distressed companies. Then, in order to select non-distress firms, we categorized those firms in different industries, and all the firms that were in that industry and their information available during the research period were classified as non-distress firms. Consequently, the statistical sample included 1790 firm-year observations. Table 1 shows the distribution of sample numbers distressed and non-distressed firms by industry and by period.

Table 1: Description of the Sample

Panel A: Industry composition for the full sample

Industry	Food	Automobile	Metal products	Non-metallic mineral products	Basic metals	Machinery & equipment	Petrochemicals & Chemicals	Total
Obs.	310	270	110	300	200	260	340	1790

Panel B: Distribution of distressed versus non-distressed firms by time for the full sample

Year	2008	2009	2010	2011	1.25	2013	2014	2015	2016	2017	Total
Distress	23	20	26	31	48	48	50	54	52	49	401
Non-distress	156	159	153	148	131	131	129	125	127	130	1359
Total	179	179	179	179	179	179	179	179	179	179	1790

3.2 Empirical Model and Variable Measurements

This study refers to the five factor components with respect to the Z-score [1] for financial distress to investigate the impact of earnings management on the predictive power of accounting-based financial distress models. The unadjusted Z-score regression model is as follows:

$$Pr\,(Y_{i,t}=1) = \beta_0 + \beta_1\,X_{1i,t-1} + \beta_2\,X_{2i,t-1} + \beta_3\,X_{3i,t-1} + \beta_4\,X_{4i,t-1} + \beta_5\,X_{5i,t-1} + \varepsilon_{i,t} \qquad (1)$$

Where: Y= 0 if the sample firm suffers financial distress during year t, 1 otherwise.
X_1= net working capital / total assets
X2 = retained earnings / total assets
X3 = earnings before interests and taxes / total assets
X4 = book value of equity / book value of total liabilities
X5 = net sales / total assets

In this study 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, equation (1) is a logistic regression model. Logistic regression makes it possible to compute a z-score for a given company, but this score is expressed as a probability of failure as follows:

$$Z = \frac{1}{1 + e^{-(W_0 + W_i X_i)}} \qquad (2)$$

Where: X_i is explanatory variables and W_i the weights which are estimated using maximum likelihood estimation. With this method, a firm is classified into a given group by comparing its probability of financial distress with a pre-determined threshold [22]. Consistent with prior study [41], to investigate whether adjustment for real activities 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:

$$\Pr(Y_{i,t}=1) = \beta_0 + \beta_1 X_{1i,t-1} + \beta_2 X_{2i,t-1} + \beta_3 X_{3i,t-1} + \beta_4 X_{4i,t-1} + \beta_5 X_{5i,t-1} + \beta_6 D\times X_{1i,t-1} + \beta_7 D\times X_{2i,t-1} + \beta_8 D\times X_{3i,t-1} + \beta_9 D\times X_{4i,t-1} + \beta_{10} D\times X_{5i,t-1} + \varepsilon_{i,t} \quad (3)$$

In the above equation, the five independent variables different from the ones for equation (1), are the products of the extent of earnings management and each of the five Z-score factors. In equation (3):
D= 1 if the proxy measure for earnings-increasing manipulation of a firm-year observation exceeds a certain threshold level, 0 otherwise. According to Gunny [29], firms with low levels of ABNCFO or ABNDISEXP and high levels of ABNPROD are identified firms of the upward real earnings management. Hence:
For H1 tests, D=1 if ABNCFO is within the bottom 25% in year t−1 and 0 otherwise.
For H2 tests, D= 1 if ABNPROD is within the top 25% in year t−1 and 0 otherwise.
For H3 tests, D=1 if ABNDISEXP is within the bottom 25% in year t−1 and 0 otherwise.
To ensure robustness, we alternately adopt 25% and 50% thresholds to identify firms with real earnings management for the financial distress forecasting model.

3.3 Real Earnings Management Proxies

For the selection of our real earnings manipulation proxies, we follow Roychowdhury's [48] methodology and focus on three metrics: the abnormal levels of cash flow from operations (CFO), discretionary expenses, and production costs and as they usually are the most significant accounts in a firm's annual report and revenues, receivables, cost of goods sold and inventory are the most frequently managed items [13, 18, 45].

Sales Manipulation: we analysis sale manipulation estimating the following cross-sectional regression (4), for each combination of industry and year identified, to calculate the normal level of cash flow given reported sales [48].

$$\frac{CFO_{i,t}}{Assets_{i,t-1}} = \beta_1 \frac{1}{Assets_{i,t-1}} + \beta_2 \frac{Sales_{i,t}}{Assets_{i,t-1}} + \beta_3 \frac{\Delta Sales_{i,t}}{Assets_{i,t-1}} + \varepsilon\varepsilon_{i,t} \quad (4)$$

Where: CFO = Cash flow from operations (calculated as earnings before interests and taxes + depreciation and amortization,+/- changes in inventories, changes in trade and other receivables, changes in trade and other payables).
ASSETS = Total assets.
SALES = Net sales.
ΔSALES = Change in net sales.

For each firm, abnormal cash flow (ABNCFO) is obtained as the difference between the actual CFO and the normal CFO calculated using the estimated coefficients from the above equation (4). The ABNCFO is a measurement of the acceleration of recognizing sales through increased price discounts or more lenient credit terms.

Production Costs Manipulation: The manipulation of production costs is analyzed by the following model (5) which is used to estimate the normal level of production costs [48]. The latter is defined as the sum of the cost of goods sold and change in inventory as it overcomes the disadvantages that would have been observed by using the value of the cost of goods sold alone, as explained in detail by Roychowdhury [48]. The same definition of production cost is also used by Gunny [29] who explicitly highlights the several benefits of this approach. The model is estimated separately for each combination of industry and year.

$$\frac{\text{Prod}_{i,t}}{\text{Assets}_{i,t-1}} = \beta_1 \frac{1}{\text{Assets}_{i,t-1}} + \beta_2 \frac{\text{Sales}_{i,t}}{\text{Assets}_{i,t-1}} + \beta_3 \frac{\Delta\text{Sales}_{i,t}}{\text{Assets}_{i,t-1}} + \beta_4 \frac{\Delta\text{Sales}_{i,t-1}}{\text{Assets}_{i,t-1}} + \varepsilon\varepsilon_{i,t} \tag{5}$$

Where: PROD =Cost of goods sold + change in inventory.
ASSETS = Total assets.
SALES = Net sales.
ΔSALES = Change in net sales.

Abnormal production costs (ABNPROD) are then the difference between actual costs and the normal level of expenses resulting from the use of the estimated coefficients from equation (5).

Decreases in Discretionary Expenses: Decreasing in discretionary expenses which include advertising expense, research, and development (R&D), and sales, general, and administrative (SG&A) expenses. Reducing such expenses will boost current period earnings. Due to the lack of accurate classification of R&D expense in corporate financial statements, total SG&A are considered to be avoidable expenses. Following prior literature [41, 48], expected the normal level of discretionary expenses are modeled for each industry and year as:

$$\frac{\text{DISEXP}_{i,t}}{\text{Assets}_{i,t-1}} = \beta_1 \frac{1}{\text{Assets}_{i,t-1}} + \beta_2 \frac{\text{Sales}_{i,t-1}}{\text{Assets}_{i,t-1}} + \beta_3 \frac{\Delta\text{Sales}_{i,t}}{\text{Assets}_{i,t-1}} + \beta_4 \frac{\Delta\text{Sales}_{i,t-1}}{\text{Assets}_{i,t-1}} + \varepsilon\varepsilon_{i,t} \tag{6}$$

Where: DISEXP = Total sales, general, and administrative (SG&A) expenses
ASSETS = Total assets.
SALES = Net sales.
ΔSALES = Change in net sales.

Abnormal discretionary expenses (ABNDISEXP) are then computed as the difference between each firm's actual discretionary expenses (SG&A) and the normal level of discretionary expenses as determined by the equation (6). We use abnormal production costs (ABNPROD) and abnormal discretionary expenses (ABNDICEXP) to gauge the presence of earnings management in the form of cost reduction, perhaps at the expense of future profits.

4 Empirical Results

4.1 Descriptive Statistics

The descriptive statistics of variables are shown in Table 2. The mean and median Z-score measures are 1.45 and 1.43, respectively. The mean working capital (WC), mean retained earnings (RE) and mean EBIT, as percentages of total assets, are -2.5%, -7%, and 8.8%, respectively. Sales are, on average, 94.2% of total assets. The average return on assets (ROA) is 8.1%. The debt ratio (DR) is approximately 84%. This means that 84% of the company's assets financed by debts. The results also show that on average, 8%, 10% and 18% of corporate assets were used to manipulate sales, production cost, and optional costs, respectively.
Table 3 shows 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 is significantly less than those of the non-distressed firms, with some even trending below zero. The 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, distressed firms on average, experience losses during the year before financial difficulties. For these firms, the mean debt ratio (DR) exceeds 140%. All of these numbers differ significantly from those of the non-distressed firms. Among the real earnings management variables, the median ABNCFO of distressed firms is negative and is significantly less than those of non-distressed firms. This result supports the notion that firms tend to time the recognition of sales before financial distress events.

Table 2: Summary of descriptive statistics.

Variable	Mean	Median	Min	Q_1	Q_3	Max	Std. dev.
Z-score	1.4512	1.4371	-12.792	0.6359	2.1322	117.733	3.5845
WC	-0.0248	0.0611	-5.5331	-0.1164	0.2089	6.5352	0.5607
RE	-0.0704	0.0447	-8.9887	-0.1129	0.1479	29.5929	0.9901
EBIT	0.0881	0.0858	-0.6632	0.0201	0.153	1.9264	0.1566
BE	0.6019	0.3883	-0.8454	0.112	0.7514	53.7443	1.6183
S	0.9419	0.8186	0.0028	0.5552	1.1315	23.0092	0.9032
ROA	0.0813	0.0535	-0.9783	-0.0056	0.1401	10.0843	0.3411
DR	0.8358	0.7189	-0.0133	0.5676	0.8998	26.3675	0.8759
ABNCFO	-0.0826	-0.0044	-107.78	-0.0886	0.085	14.221	2.843
ABNPROD	0.1003	-0.0009	-9.4994	-0.1232	0.1182	45.3729	1.7159
ABNDISEXP	-0.1865	0.0102	-1.8131	-0.0226	0.0478	1.7687	1.9795

Source: Research Results.

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	-0.3855	2.0069	-2.3924	-16.2530***	0.011	1.7054	-1.6944	-24.349***
WC	-0.4754	0.1026	-0.5780	-12.3765***	-0.2493	0.1144	-0.3637	-19.642***
RE	-0.7131	0.1113	-0.8244	-12.8115***	-0.3276	0.0855	-0.4131	-26.335***
EBIT	-0.0433	0.1253	-0.1686	-19.8067***	-0.0189	0.1053	-0.1242	-19.879***
BE	-0.0152	0.7763	-0.7915	-12.0005***	-0.0665	0.5043	-0.5708	-23.709***
S	-0.6736	1.0178	-0.3442	-9.2473***	0.5946	0.8652	-0.2706	-10.687***
ROA	-0.0882	0.1291	-0.2173	-13.3549***	-0.0952	0.0813	-0.1765	-21.569***
DR	-1.4059	0.6746	0.7313	8.5293***	1.0728	0.6614	0.4114	23.809***
ABNCFO	-0.0277	-0.0975	0.0698	0.7156*	-0.0184	0.0009	-0.0193	-2.696***
ABNPROD	-0.1033	0.0995	0.0038	0.0547*	0.0299	-0.0096	0.0395	3.578***
ABNDISEXP	-0.0142	-1.5044	1.4902	1.0055**	0.0103	0.0102	0.0001	0.378

As a result, their CFOs are less than the estimates derived from the comparison group. Moreover, median ABNPROD of distressed firms is positive and greater than those of non-distressed firms, as well as, mean ABNDISEXPs of distressed firms are greater than those of non-distressed firms, indicating that distressed firms tend to report lower cost through both overproduction and decrease of discretionary expenses to boost their earnings.

4.2 Effect of Earnings Management on the Accounting 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 Table 4 and 5, respectively. Table 4 reports that, except for WC, the estimated coefficients for the data sample are largely the same as the Z-score coefficients reported by Altman [1]. Specifically, the coefficient is the greatest for EBIT and the lowest for BE. Moreover, with the exception of WC, the factors exhibit 5% statistical significance.

Table 4: Regression Results of the Altman Z-score Model.

Altman (1983)	Variable	Controlled for the year effect		Not controlled for the year effect	
		$\chi2$	Est. coeff.	$\chi2$	Est. coeff.
WC	0.717	-0.2567	-0.97	-0.2038	-0.74
RE	0.847	6.4037	10.76^{***}	6.3157	10.43^{***}
EBIT	3.107	4.2522	3.99^{***}	4.3830	4.06^{***}
BE	0.42	0.5012	2.26^{**}	0.4834	2.17^{**}
S	0.998	0.5763	2.87^{***}	0.5916	2.91^{***}
Cons		1.0468	4.78^{***}	1.6131	4.45^{***}
LR statistic		822.77^{***}		811.23^{***}	
R-square		.49		.48	
Obs.		1790		1790	

Panel A of Table 5 shows whether the acceleration of recognizing sales to boost revenue affects the specification of the financial distress prediction model. Regardless of the inclusion of year effects, ABNCFO exhibits a significantly negative effect on the slope coefficient the retained earnings to total assets ratio (D×RE) for both the 25% and 50% thresholds for earnings management, and a negative effect on the coefficients for asset turnover (D×S), the coefficients for the working capital to total assets ratio (D×WC), and the leverage ratio (D×BE) for the 25% threshold 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 balance sheet and are not heavily affected by the current sales, which is a temporary line item in the comprehensive income statement.

However, the negative Coefficients of D×S, D×WC, and D×BE suggest that the predictive role of asset turnover, working capital and leverage is reduced for firms with the acceleration of recognizing sales. 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. Thus, the predictive role of accelerating sale recognition is reduced. Accelerating also recognition of sales does not significantly affect the coefficients for the earnings before interest and taxes to total assets ratio (D×EBIT). In general, except for the earnings before interest and taxes to total assets ratio, the results indicate that real earnings management by accelerating the recognition of sales affects the roles of retained earnings ratio, turnover factors, working capital ratio, and the leverage ratio in the Z-score model. Significance of likelihood ratio statistics indicates the overall significance of the fitted regression model at a 99% confidence level.

Panel B of Table 5 presents the extent to which manipulative reductions in CGS to boost earnings by firms affects the Z-score model in predicting firm distress.

Findings show that ABNPROD has a positive effect on the explanatory power of the accumulated earnings ratio (D×WC) and a negatively effect on the coefficient for leverage (D×BE) the 25% and 50% thresholds for earnings management in firm's probability of survival.

Table 5: Regression Results with Adjustments for Real Earnings Management

Variable	Not controlled for year effect				Controlled for year effect			
	Threshold				Threshold			
	D25		D50		D25		D50	
	Est. coeff.	χ^2	Est. coeff.	χ^2	Est. coeff.	χ^2	Est. coeff.	χ^2
Panel A: Abnormal cash flows as the proxy for real earnings management								
Cons	.9486	3.95***	1.337	5.77***	1.553	3.94***	1.98	5.09***
WC	0.407	0.12	0.805	0.11	0.05	0.15	0.234	0.31
RE	8.699	10.73***	9.845	8.89***	8.773	10.60***	9.714	8.70***
EBIT	3.1312	2.02**	1.627	0.80	3.219	2.04**	1.543	0.74
BE	0.124	0.73	0.388	1.09	0.099	0.60	0.342	0.98
S	1.102	3.76***	0.856	2.63***	1.083	3.66***	0.859	2.59***
D×WC	-2.397	-2.08**	-0.038	-0.05	-2.256	-1.95***	-0.238	-0.29
D×RE	-3.863	-2.81***	-2.828	-2.15**	-4.056	-2.93***	-2.661	-2.01**
D×EBIT	0.891	0.36	2.422	0.98	1.142	0.45	2.752	1.09
D×BE	5.63	4.46***	-0.077	-0.19	5.719	4.50***	-0.048	-0.12
D×S	-1.221	-3.88***	-0.48	-1.50	-1.198	-3.77***	-0.47	-1.46
LR statistic	888.05***		856.96***		900.38***		867.08***	
R-square	0.5505							
Panel B: Abnormal production costs as the proxy for real earnings management								
Cons	1.2785	5.56***	1.3143	5.60***	1.9519	5.05***	1.9923	5.05***
WC	-0.8178	-0.59	-0.0057	-0.01	-0.6740	-0.49	0.0728	0.13
RE	5.8597	3.58***	5.7847	6.87***	5.6135	3.64***	5.6206	6.52***
EBIT	0.4609	0.18	4.2455	2.62***	0.8001	0.31	4.5999	2.82***
BE	3.3862	2.55**	0.9250	2.25**	3.5187	2.60***	0.9536	2.26**
S	0.1990	0.49	0.3047	1.16	0.1441	0.35	0.2934	1.10
D×WC	0.7992	0.56	0.0070	0.01*	0.6872	0.48	-0.0399	-0.06
D×RE	2.4829	1.51*	4.7454	3.78***	2.7130	1.64*	4.8289	3.82***
D×EBIT	3.8082	1.35	-1.6994	-0.73	3.5825	1.25	-2.0689	-0.88
D×BE	-3.1604	-2.38**	-0.8088	-1.86*	-3.3280	-2.46**	-0.8792	-2.00**
D×S	0.3373	0.82	0.4423	1.51*	0.4091	0.98	0.5043	1.70*
LR statistic	857.96***		863.80***		869.02***		874.48***	
R-square	0.5318		0.5355		0.5387		0.5421	
Panel C: Abnormal discretionary expense as a proxy for real earnings management								
Cons	1.2776	5.40***	1.1932	5.13***	1.8246	4.69***	1.6946	4.34***
WC	-0.0096	-0.02	-0.4161	-1.44	0.0589	0.12	-0.5785	-1.87**
RE	8.7491	9.85***	6.3956	7.22***	8.7358	9.58***	6.4901	7.05***
EBIT	3.7366	2.46**	4.3538	2.59***	3.8078	2.49**	4.1757	2.42***
BE	0.8589	2.52**	1.7172	3.51***	0.8403	2.44**	1.8775	3.72***
S	0.4557	1.89*	0.1655	0.68	0.4732	1.96**	0.2069	0.84
D×WC	-0.3466	-0.42	0.7138	1.57	-0.3212	-0.14	0.8905	1.93**
D×RE	-2.4280	-1.92*	2.8033	2.28**	-2.6502	-2.09**	2.9116	2.30**
D×EBIT	-0.3147	-0.13	-1.6696	-0.71	-0.0232	-0.01	-0.9297	-0.39
D×BE	-0.9340	-2.55**	-1.7035	-3.42***	-0.9208	-2.51***	-1.8624	-3.63***
D×S	0.1209	0.42	0.7339	2.45***	0.1062	0.36	0.7634	2.52**
LR statistic	861.14***		874.36***		872.28***		886.99***	
R-square	0.5338		0.5420		0.5407		0.5498	

***, **, and * denote significance at the 1%, 5%, and 10% levels in two-tailed tests, respectively.
Source: Research Results.

In addition, earnings management through overproduction has a positive and significant effect on the coefficient of turnover ratio (D×S) at a 50% threshold, but this result is not statistically significant at the 25% threshold. Working capital refers to the difference between current assets and current debt. If the company uses a different method of valuing inventory to transfer the CGS to end-of-period inventory, current assets increased and in result increases in 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. The significance of likelihood ratio statistics indicates the overall significance of the fitted regression model at a 99% confidence level. Panel C of Table 5 reports the effects of the real earnings management through 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 EBIT of firms with greater discretionary expense plays a less significant role in forecasting survival or distress. But this role is not significant. The reduction in discretionary expenses (i.e.: SG&A) increases concurrent earnings but may result in future profit reductions. Moreover, earnings management in the form of reduced discretionary expenses negatively affects the explanatory power of D×RE and D×BE. This means that the more SG&A decrease, lead to increase the leverage (BE). In sum, the results indicate that the reduction in discretionary expenses affects the roles of the retained earnings and leverage in the Z-score model. The significance of likelihood ratio statistics indicates the overall significance of the fitted regression model at a 99% confidence level.

4.3 Model Evaluation

Testing whether the inclusion of real earnings management variables improves the predictive validity of our financial distress prediction model, we assessed our model's error rate and compared it with the traditional accounting-based financial distress model. The financial distress prediction literature identified two error types. The model can predict that a firm is not distress when, in fact, it is. This error corresponds to the assignment of a high credit score to firms that distress (type I error).

Table 6: Classification Tables

Sample	Obs.	Performance	Traditional model	EM type		
				ABNCFO	ABNPROD	ABNDISEXP
Distress	401	sensitivity	65%	69%	64%	68%
		Type-I error	35%	31%	36%	32%
Non-distress	1389	specificity	96%	98%	97%	98%
		Type-II error	4%	2%	3%	2%
Correctly classified			89%	92%	90%	91%

Source: Research Results.

A type II error occurs when the model misclassifies a non-distress firm as a distress one. We used the Table classification approach to assess whether our real earnings manipulation proxies improved the predictive ability of the distress prediction model and reduced type I errors, which are costlier than a type II errors [38]. We began by running the Z-score [1] model, as well as the Z-score [1] model supplemented with real earnings management proxies. Next, we defined the classification matrix. Table 6 shows our estimated models' predictive ability. The sensitivity of a model describes the probability that the model will, given a specified probability (cut-off point) when it is distress, classify a firm as distress. The specificity of a model refers to the probability that the model classifies a firm as non-distress when it is non-distress. Since our panel sample was unbalanced, we adjusted the cut-off point as a percentage of the distress firm-year observations scaled according to the total firm-year observations in the sample. We used a cut-off point of 0.6 to calibrate accuracy.

The classification Tables show that the model with real earnings management proxies provided a higher sensitivity rate (lower type I errors) than the models without them. The results specifically provide evidence that the financial distress model, which includes the real earnings management indicators, is the best model in terms of sensitivity (69%) and specificity (98%), thereby indicating that it is particularly suitable for identifying distress firms. Our findings also show that the model, which includes real earnings manipulation proxy variables, provides a higher overall classification rate (92%) than the traditional model. These findings support research hypotheses, namely that the inclusion of the real earnings management indicators improves the accounting-based distress prediction model's predictive power.

5 Discussion and Conclusions

In the literature on earnings management, there is strong evidence that managers of distressed companies manipulate their financial statements to increase earnings. In this study, we explore that taking into account financial reports potential manipulation enhances the accounting-based scoring model's predictive power. We expanded Z-score [1] distress prediction model with real earnings management Proxies. Our analyses provide evidence that real earnings management is predictive signals of financial distress. Our findings also suggest that earnings management can be applied to increase the predictive ability of accounting-based financial distress prediction models, which are used in academic research and in practice. This paper contributes to studies about financial distress prediction. We show that the inclusion of real earnings management enhances the predictive accuracy of the accounting-based prediction model. The results indicate that the adjusted model with earnings management has strong predictive power and can accurately discriminate - over a long period of time- between distress firms and non-distress firms. Thus, other financial information about a firm can effectively complement the financial ratios, which are commonly used [3].

Overall, these findings have practical implications and can be of interest to banks and financial institutions. Banks and financial institutions (such as rating agencies, investment funds, and pension funds) use bankruptcy prediction models- which closely follow those known in the scientific literature- for their credit ratings. The entire lending and investment strategy are based on such ratings. Therefore, an improvement in the predictive ability of credit rating and bankruptcy forecasts enhances the proper allocation of financial resources and reduces the costs of misclassifying distress firms as non-distress firms (type I errors), which result in investment losses and an increase in the banks' non-performing loans. The reduction of type I errors is a key objective for banks since these are much costlier than type II errors (non-distress firms misclassified as firms that distress; Cenciarelli et al. [14]. This finding is in agreement with the results of Cenciarelli et al. [14] and Du Jardin et al. [22] studies.

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