A Generic Model Of Predicting Probability Of Success-Distress Of An Organization: A Logistic Regression Analysis

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ABSTRACT

Many bankruptcy prediction models have been created over the years using a mix of variables derived mostly from accrual-based accounting statements and were industry specific. The primary issue with using a model comprised of accrual-based variables is that firm management can manipulate different components and make the balance sheet and income statement misleading (Wanuga 2006). Thus, firms appear financially healthy yet unable to meet the day-to-day cash flow needs of the firm; these financial issues are less likely to be hidden in the cash flow statement (Sharma 2001). In this study, we use a binary regression model with theoretically supported variables obtained from the cash flow statement to forecast firm success versus distress. Of particular interest, we examine firms representing 85 industries using firm data during and immediately following the greatest recession in United States history (Fieldhouse 2014; Lee 2014). The model is generic in the sense that it can be used to predict the probability of success-distress of any entity using the three major financial statements. We find that the overall model correctly classifies organizations 90.290 percent of the time.

Keywords: Bankruptcy Model; Forecast; Financial Distress; Prediction

INTRODUCTION

A variety of techniques and measures are used to assess the performance of profit and nonprofit organizations. Over the years, many models have been created to predict the failure, bankruptcy, insolvency or distress of profitable companies using a multiple discriminant analysis (MDA), which is a commonly used technique. A high number of the studies implement predictor variables, or financial ratios, that are developed from the balance sheet and income statement (i.e., accrual-based financial statements) rather than the statement of cash flows. In an MDA, it is assumed that predictor variables are measured on a continuous scale and their distribution is multivariate normal. It is also assumed to have a common covariance matrix across dependent variables. Another multivariate technique, the logit regression analysis (LRA), has not been used as often by researchers. The LRA allows predictors to be continuous, categorical or a mix of both and does not assume normality of continuous explanatory variables. Moreover, the LRA technique is more robust than MDA and is appropriate for a wider class of distribution (Lo 1986).

The recession of 2008-2012 forced an unusually high number of businesses to declare bankruptcy (Fieldhouse 2014; Lee 2014). Hence, this new dataset of failed companies deserves a fresh look. The purpose of this paper is to use logit analysis to construct a success-distress prediction model by using a more recent dataset. The noteworthy points of this study are many. First, the firm sample is *not* a focused group-- it contains 85 firms with different 4-digit SIC codes (refer to the Appendix). In other words, this model is generic in nature and *not* industry specific. Second, we selected logically justified predictor variables that are not the result of a step-wise procedure or a data mining approach. Third, all predictor variables use the cash flow from operations (CFO) value, which is on the cash flow statement (CFS). Finally, all distressed and successful competitor firms included in our test sample are from the 2008-2015 period.

The paper is organized as follows. The literature review is provided in the next section while the model and data descriptions are provided in the third and fourth sections. The results and analysis are discussed in the fifth section.

The sixth section shows how to use our model to predict the probability of success-distress of a few sample organizations. The final section is the summary and conclusion of the paper.

LITERATURE REVIEW

For more than forty years, business failures have been predicted using country-specific datasets and univariate and multivariate techniques. The Altman, Halderman, and Narayanan (1977) paper identifies 22 countries where comparable studies were completed. Although discriminant analysis is a commonly used technique, logit analysis is also a popular technique (e.g., Zavgren & Friedman 1988; Aziz, Emanuel, & Lawson 1988; Laitinen 1994; Gentry, Newbold, & Whitford 1985a; Gilbert, Menon, & Schwarts 1990). Other review articles in which the authors evaluated and compared popular bankruptcy prediction models include Zavgren (1983), Barnes (1987), Begley, Ming, & Watts (1996), Sharma (2001) and Agarwal and Taffler (2007). Some attempts were made to construct CFO-based prediction models (e.g., Aziz et al. 1988; Kahya 1997; Gentry et al. 1985; Rujoub, Cook, & Hay 1995; Aziz & Lawson 1989; Cornelius 1985; Gombola, Haskins, Ketz, & Williams 1987). Siegel and Akel (1989) and Sharma (2001, 21) reviewed articles which used cash flow based measures to predict business failure. Sharma concluded that "[d]espite numerous failure prediction studies investigating the ability of cash flow information to predict corporate failure, their results are mixed and hence inconclusive." Bellovary, Giacomino, & Akers (2007) is an excellent source of review of bankruptcy prediction studies for 1965- 2005 period.

Bellovary (2007) shows that very few studies have used bankrupt or distress prediction models with variables comprised of CFS information and assessed them using a logistic regression analysis (LRA) since the 1980s. However, those that have used the models and analysis technique have provided evidence that predictors using cash flow from operations have information value.

Gentry, Newbold, and Whitford (1985b) evaluate bankruptcy predicting components in terms of cash inflows and outflows over a one-year period and a three-year period average, and used "major net funds flow components" to do so (9). The authors find the components that best predict problems one year prior to distress, in order, are cash outflows of dividends, receivables, and investments; those for the three-year average that best predict failure are dividends, total net flow divided by total assets, and other assets and liability flows not included in other variables. Based on their work, the argument for using cash flows in predictor variables for distressed versus successful firms is strengthened. Specific variables using cash flows from operations is also supported by the Gilbert, Menon, and Schwartz (1990) study.

Gilbert, Menon, and Schwartz (1990) examine the model of CFS-based variables by Casey and Bartczak (1985) and the model of accrual accounting-based variables by Altman (1968) to determine the information value of each in distinguishing between healthy firms, at risk firms that survive and those that fail. Overall, the authors use LRA and a determined set of six factors to distinguish between groups that have accuracy rates as high as 62.50 percent for bankrupt firms and 97.90 percent for non-bankrupt firms. They find that healthy, distressed and bankrupt firms are distinguished best by CFO divided by total liabilities, which has more information value than suggested by the prior literature, e.g., Casey and Bartczak (1985).

Bhandari (2014) also compared and contrasted the Altman (1968) and Bhandari and Iyer's (2013) bankruptcy prediction models. Both papers use a discriminant analysis technique on matched sample of firms, yet the papers differ in all other respects. Altman (1968) uses firm data of publically-traded manufacturers and only accrual-accounting based financial ratios. Conversely, Bhandari and Iyer (2013) uses firm data from over 25 industries and a mixture of predictor variables derived from all three financial statements. Similar to a data mining technique, Altman developed and assessed 22 predictor variables, selected the five best, and justified the selected variables post-facto. In contrast, Bhandari and Iyer (2013) logically justified (a-prior) and evaluated seven explanatory variables. Table I summarizes the comparisons (16).

Giacomino and Mielke (1993) argue that a performance evaluation can be conducted using cash flow ratios by assessing a firm in terms of sufficiency and efficiency. How well a firm's cash flows meets its needs is described by sufficiency ratios. For example, the cash flow adequacy ratio "directly measures a company's ability to generate cash sufficient to pay its debts, reinvest in its operations and make distributions (dividends) to owners" (56). The adequacy of a firm's ability to earn cash in comparison to other periods and the industry is characterized by efficiency ratios, which are the cash flow to sales, operations index, and cash flow return on assets. A form of each of these variables are used in this study and are further discussed below. Although the authors' model is limited to three industries, electronics, food, and chemical, they find that the best ratios to define the performance of a firm are cash flow adequacy, cash flow to sales, and cash flow return on assets. However, only the cash flow to sales ratio distinguished between performances across the three industries.

When comparing bankruptcy prediction models, the CFS-based models are more practical. Cash flow "information has significant information content over accrual information in assessing the predicted probability of failure" (Sharma 2001, 4). Yet, Sharma noted in his paper that prior studies using CFS-based models had mixed or inconclusive results for the following reasons: (1) failed to properly measure CFO; (2) lack of model validation; (3) used old data; (4) ignored some important components of the CFS or variables; and (5) lack the ability to be replicated. Each of the failures in prior studies, as identified by Sharma, are addressed in this study.

THE MODEL

A success-distress prediction model was created using a Logit Regression Analysis (LRA), which is a process that reduces multiple measures to a single weighted composite score, z_i, that can be used to distinguish between two group members of two groups and estimate the probability of fitting in one group over another (Sharma, 1996). In cases using two groups, a multivariate analysis is reduced to a simple univariate.
Mathematically, LRA obtains coefficients (a_is) of financial ratio or predictor variables (x_is) in a linear equation, such as that in equation 1,

$$ln\left(\frac{p_i}{1-p_i}\right) = z_i = a_0 + a_1x_1 + a_2x_2 + \cdots a_nx_n, \tag{1}$$

which minimizes error sum of square. The predicted probability of failure 'p_i' is then calculated using equation 2,

$$p_i = \left(\frac{e^{zi}}{1+e^{zi}}\right) x\ 100 \tag{2}$$

where e is the base of the natural logarithm and z_i is the predicted (logit) score.

The primary objective of this model is to predict whether the assessed organization is distressed or not, signaling stakeholders that the organization has a higher probability of failure in the near future. Multicollinearity among independent variables does bias the relative importance of each variable; however, in a descriptive-predictive model, one should refrain from giving undue importance to the estimated coefficient.

DATA

A list of "inactive" firms was obtained from COMPUSTAT to select approximately 90 "failed" or "distressed" firms from the 2008-2015 period. Each of the distressed firms was matched with a "successful" firm of comparable size (e.g., sales or total assets) in the same Standard Industrial Classification (SIC) code. All financial data for the fiscal year prior to the inactive year was obtained from the COMPUSTAT database. Of the 85 industries represented in the analysis, the industries most represented are prepackaged software services, women's clothing retail stores and videotape rental services (*5.154, 4.571 and 3.429 percent, respectively*). For more information pertaining to the industries, refer to Appendix A.

PREDICTOR VARIABLES

The proposed model is generic in the sense that it can be used to predict the probability of success-distress of any organization for which three basic (audited) financial statements are publicly available. The binary dependent variable is an inactive or distressed firm is represented by a zero (0) and an active or success firm is one (1). We selected cash flow based explanatory variables to construct the logit model. The five cash flow metrics used as predictor variables are as follows:

1) Operating cash flow / current liabilities
2) Cash flow coverage of interest
3) Operating cash flow margin
4) Operating cash flow return on total assets
5) Earning Quality

The rationales for selecting the above-mentioned metrics to use in our LRA model are as follows:

X_1 Operating cash flow / current liabilities (CFO / CL): This ratio measures a company's liquidity or its ability to pay short-term obligations (Bhandari & Iyer, 2013; Dennis, 1994; Figlewics & Zeller, 1991; Mills & Yamamura, 1998; White, Ashwinpaul, & Fried, 1997; Wild, Bernstein, & Subramanyam, 2001). If a company has a high value for this ratio, then it is less likely to fail.

X_2 Cash flow coverage of interest ((CFO+INT+TAX) / INT or INT COVERAGE): When a company is struggling, sometimes creditors will allow it to temporarily pay the interest on a loan. However, depending on the situation, if a company is unable to meet that minimum obligation it may be forced into technical bankruptcy (i.e., going concern) (Johnstone, Gramling, & Rittenberg, 2015). This ratio is similar to the accrual-based Times Interest Earned (TIE) ratio in that it measures the financial strength of a firm; however, the cash flow coverage of interest ratio is measured using more economically sensitive information from the cash flow statement. Specifically, the numerator is the operating cash available to a firm prior to paying interest and taxes, and the denominator is the interest for short- and long-term debt (Bhandari & Iyer, 2013; Carslaw & Mills, 1991; Figlewics & Zeller, 1991; Fraser & Ormiston, 2010; Mills & Yamamura, 1998; Stickney & Brown, 1999; White et al., 1997). The higher the value for this specific ratio, the less likely the firm is to default on meeting the minimum obligation.

X_3 Operating cash flow / sales (CFO / NET SALES): Similar to the traditional profit margin ratio, this ratio measures the percentage of operating cash earned from sales and is a better measure for assessing profitability of operations or firm liquidity than the traditional financial statement ratios (Bhandari & Iyer, 2013; Carslaw & Mills, 1991; Dennis, 1994; Figlewics & Zeller, 1991; Fraser & Ormiston, 2010; White et al., 1997). This ratio is calculated by dividing CFO by net sales. A higher value in this ratio is more desirable because it signals that the firm is profitable in its day-to-day operations.

X_4 Operating cash flow return on total assets (CFO / TA): Financially healthy companies are better able to generate cash more efficiently from its assets obtained through creditor and investor financing (Bhandari & Iyer, 2013; Figlewics & Zeller, 1991; Fraser & Ormiston, 2010; White et al., 1997). This ratio is similar to the conventional return on assets (ROA) in that it uses total assets in the denominator; rather than using the net income as the numerator, as in the ROA ratio, this ratio uses CFO. Consistent with the previous cash flow based ratios, a higher value is more desirable.

X_5 Quality of earning (EBIT/CFO): Successful companies are better able to meet stakeholders' expectations (i.e., analysts' forecasts) and more conservative in reported earnings suggesting the company has higher earnings quality (Fraser & Ormiston, 2010; White et al., 1997; Wild et al., 2001). Consistent with the method used by Bhandari and Iyer (2013), we use the accrual-based accounting value from operating income (i.e., earnings before interest and taxes or EBIT) as the numerator and CFO as the denominator (Bhandari & Iyer, 2013). Companies that have a value of one or less for this ratio are more likely to use conservative reporting measures and less likely to have financial difficulty.

RESULTS AND ANALYSIS

SPSS-22 software was used to perform binary logistic regression analysis. Below are tables showing descriptive statistics, a univariate test of significance, classification percentages, and the individual probability of group membership.

Predictor variable means (standard deviations) for successful and distressed firms are presented in Table 1. All means for the successful companies are positive while all of those of distressed firms' means are negative, except that for X_5, EBIT/CFO. Overall, successful firms are more liquid (X_1), able to cover interest on debt (X_2), convert sales to cash (X_3), generate a return on assets (X_4), and have quality earnings (X_5). On the other hand, distressed firms have lower liquidity (X_1) and are less able to cover interest on debt (X_2), convert sales to cash (X_3), generate a return on assets (X_4) and have lower quality earnings (X_5).

Further analyses show that the means of the successful and distressed firms are statistically significant ('t' test) for the variables of CFO/CL, CFO/SALES and CFO/TA. The INT COVERAGE and EBIT/CFO variable means do not differ statistically. The results for INT COVERAGE may be attributable to all firms ensuring that interest on debt is covered to minimize the likelihood of technical default. The EBIT/CFO results suggest that firms' management may have been working harder to meet predictions and analysts forecasts during the economically challenging period.

Table 1. Descriptive Statistics

No.	Predictor Variables	Successful Firms		Distressed Firms		't' test
		Mean	Std. Dev.	Mean	Std. Dev.	
X_1	CFO/CL	0.805	0.911	-0.227	0.811	0.000
X_2	(CFO + INT + TAX)/ INT	685.015	5,084.507	-11.454	72.964	0.221
X_3	CFO/SALES	0.243	0.614	-2.004	9.890	0.030
X_4	CFO/TA	0.131	0.113	-0.100	0.333	0.000
X_5	EBIT/CFO	1.090	1.167	1.447	2.481	0.215

The 175 firms were assessed using a binary logistic regression, and we find that the model is statistically significant *(χ^2 (5) = 154.781, p = 0.000)* (refer to Table 2). Results show that firms' ability to cover current debt (X_1), interest expenses (X_2), and generate a cash from sales (X_3) are significant *(p = 0.035, p = 0.006* and *p = 0.038, respectively)* although companies' progress on generating cash from all assets (X_4) and make quality earnings (X_5) are not (*p = 0.783* and *p = 0.257, respectively)*. The lack of significant findings in generating cash from all assets (X_4) and ability to generate quality earnings (X_5) may be due to the greatest economic recession in the United States. The recession "officially began in December 2007 and ended in June 2009" (Fieldhouse, 2014, 1); however, the economic recovery has been very slow causing once healthy companies to fail (Lee, 2014 and The Center for Financial Innovation and Stability, 2016).

Table 2. Variables in the Equation (2008 to 2015 Period)

No.	Predictor Variables	Beta	SE	Wald	Sig.	Expected Beta
	Constant	-2.636	0.512	26.542**	0.000	0.072
X_1	CFO/CL	3.093	1.468	4.437**	0.035	22.047
X_2	(CFO + INT + TAX)/ INT	0.263	0.096	7.502**	0.006	1.301
X_3	CFO/SALES	7.306	3.512	4.327**	0.038	1,488.520
X_4	CFO/TA	2.020	7.337	0.076	0.783	7.539
X_5	EBIT/CFO	0.108	0.095	1.285	0.257	1.114

Overall, the model is statistically significant (X^2 (5) = 154.781, p-value = 0.000, Nagelkerke R-square = 0.784). In Table 02, expected beta values, also known as the odds ratio, are predicted by the model. The value 22.047 for the CFO/CL ratio means that the odds of this ratio to predict business success are 22 times better than to predict distress. In contrast, this also means that the interest coverage has the lowest prediction value, which is consistent with the univariate test of significance output. In the follow-up analysis, all predictor variables are significant except for the interest coverage variable; the lack of significance for this variable was expected considering it is the last expense to be left unpaid.

More importantly, the model correctly classifies 70 out of 81 successful firms (86.420 percent) and 88 out of 94 unsuccessful companies (93.617 percent). Overall, the model correctly categorizes 90.290 percent of the time, which is better than the "by chance" criterion of 50 percent (Refer to Table 03). Sharma (2001) noted that prior studies have failed to cross-validate results and that there may be an upward bias in those results when a model is tested using the original sample data. To determine whether we have a similar issue, the model was evaluated for cross-validity using a leave-one-out-estimate analysis (LOOE), which is an unbiased estimation of classification accuracy.

Table 3. Classification Results for Binary Logistic Regression (2008 to 2015 Period)

Observed Group Members		Predicted Group Membership		Total
		Successful	**Distressed**	
Count	Successful	70	11	81
	Distressed	6	88	94
	Total	99	76	175
Percentage	Successful	86.420 %	13.580 %	93.600 %
	Distressed	6.383 %	93.617 %	86.400 %

A leave-one-out-estimates (LOOE) method of classification is comprised of many procedures that are completed using a computer program.[1] First, data is formatted using Excel. Second, the LOOE program is opened and the file location, identifying information and analysis criteria are entered. The program removes an observation and performs linear classification functions on the remaining units (*N-1*). Third, the functions are used to classify the deleted unit into a group. Finally, the process is repeated for an unknown number of iterations to create hit-rate estimates, which are based on the "proportions of deleted units correctly classified" (Huberty 1994, 88). This method is similar to that which is also referred to as the "jackknife" method (Bellovary et al. 2007, 7).

The program also generates the *McNemar's Z*, which is a standardized test statistic on how well the model predicts group membership. We find a significant difference (*McNemar's Z = -2.320, p = 0.020*); the group membership correctly predicted by the model is statistically higher than that of the observed group membership correctly predicted. In other words, the results statistically support that the model is fairly accurate in its prediction of successful versus distressed firms. Specifically, Table 04 shows that 80.570 percent of the observed group was correctly matched to the predicted group while only 10.860 percent of the observed group were incorrectly matched to the predicted group. According to the LOOE analysis, the overall hit-rate is 82.290 percent.

Table 4. Leave-One-Out Estimates Classification Results (2008 to 2015 Period)

Observed Group Members		Predicted Group Membership		Total
		Incorrectly Predicted	**Correctly Predicted**	
Count	Correctly Predicted	12	141	153
	Incorrectly Predicted	19	3	22
	Total	31	144	175
Percentage	Correctly Predicted	6.860 %	80.570 %	100 %
	Incorrectly Predicted	10.860 %	1.710 %	100 %

APPLICATION OF THE MODEL

Gilbert et al. (1990) states, a "stronger case for information value [can] be made if such models discriminate between 'at risk' firms that survive and 'at risk' firms that fail" (161). The strength of this model and a primary weakness of other success/distress models is that any stakeholder can use this model to predict the success/distress probability of any organization in which the financial information is available.

In the linear equation form, the success/distress LRA model can be written as it is in equation 3:

$$Z_i = -2.636 + 3.093\frac{CFO}{CL} + 0.263\ \frac{CFO+INT+TAX}{INT} + 7.306\ \frac{CFO}{SALES} + 2.020\ \frac{CFO}{TA} + 0.108\ \frac{EBIT}{CFO}. \qquad (3)$$

The Z_i value is then converted into the probability of success/distress by using equation 4,

$$p_i = \left(\frac{e^{zi}}{1+e^{zi}}\right) x\ 100. \qquad (4)$$

The following step-by-step approach can be used to predict the probability of success for an entity:

1) Obtain audited financial statements of the organization.
2) Extract seven variables: cash flow from operations (CFO), current liabilities (CL), interest expense (INT), tax expense (TAX), net sales (SALES), total assets (TA), and earnings before interest and tax (EBIT). Note: The interest and tax expense values may be reported as negative values; this information should be verified prior to using them in the calculation.
3) Calculate the predictor variables using the following formulas: CFO/CL; [(CFO+INT+TAX)/INT]; CFO/SALES; CFO/TA; and EBIT/CFO.
4) Insert the calculated values of the predictor variables in Step No. 4 into equation 3 (above) and calculate the value of the dependent variable, Z_i.
5) Calculate p_i using equation 4. If the probability value is high (above 50 percent), it indicates that the entity has a probability of success in the following period.

The five steps listed above are applied to three different type of companies: 1. J. C. Penney, a for-profit publicly traded corporation, 2. The Center for Nonprofit Management Inc., a nonprofit organization and, 3. The City of Detroit, Michigan, a local government entity.

EXAMPLE NO. 1 – J. C. PENNEY COMPANY, INC.

An online search for "audited financial statements for JC Penney" was completed to obtain the data for the publically traded entity. The most recent audited financial statements are available for the fiscal year ended January 30, 2016. The information needed to complete the model was collected and is presented in Table 5.

Table 5. Partial Audited Financial Statements for J. C. Penney Company, Inc.

Audited Financial Data (*in millions*)	**Values**
Cash flow from operations (CFO)	$440
Current liabilities (CL)	4,018
Interest expense (INT)	415
Tax expense (TAX)	9
Net sales (SALES) (or Total Adjusted Revenue)	12,625
Total assets (TA)	9,441
Earnings before interest and tax (EBIT)[2]	(89)

Table 6. Predictor Variables in for J. C. Penney Company, Inc.

No.	**Predictor Variable**	**Value**
X_1	CFO/CL	0.110
X_2	(CFO + INT + TAX)/ INT	2.082
X_3	CFO/SALES	0.035
X_4	CFO/TA	0.047
X_5	EBIT/CFO	(0.202)

The information in table 5 was entered into the equation (3) to calculate the dependent variable Z, which equals – 1.434 (refer to Equation 5). The values obtained in calculating the predicted value are presented in Table 6.

$$Z_i = -2.636 + 3.093\frac{440}{4.018} + 0.263\ \frac{(440+415+9)}{415} + 7.306\ \frac{440}{12{,}625} + 2.020\ \frac{440}{9{,}441} + 0.108\ \frac{-89}{440} = -\ 1.434 \quad (5)$$

Now that the dependent variable is known, it is entered into equation (4) to calculate the probability of success for the organization.

$$p_i = \left(\frac{e^{-1.43}}{1+ e^{-1.43}}\right) x\ 100 = 19.250 \quad (6)$$

Based on our model and calculations, J.C. Penney Company, Inc. has a 19.250 percent probability of success in the following year. Considering the generalized nature of the model, we randomly selected two other non-publically-traded entities to illustrate the ease of using the model when the necessary financial data is available.

EXAMPLE NO. 2 – THE CENTER FOR NONPROFIT MANAGEMENT, INC.

An online search for "audited financial statements of a nonprofit organization" was completed. The first nonprofit organization with current audited financial statements to be presented by the search engine (and randomly selected) was The Center for Nonprofit Management Incorporated, a Dallas, Texas, organization with statements dated March 31st, 2015 (The Center for Nonprofit Management Incorporated 2015). Some nonprofit organizations, such as in this case, refer to the Balance Sheet as the "Statement of Financial Position" and the Income Statement as the "Statement of Activities and Changes in Net Assets." The information needed to populate the predictor variables in equation 3 was selected and entered into Table 7.

Table 7. Partial Audited Financial Statements for The Center for Nonprofit Management Inc.

Audited Financial Data *(in millions)*	**Values**
Cash flow from operations (CFO)	$0.34
Current liabilities (CL)	0.35
Interest expense (INT)	0.01
Tax expense (TAX)	0.00
Net sales (SALES) (or Total Adjusted Revenue)	2.36
Total assets (TA)	0.77
Earnings before interest and tax (EBIT)	0.94

Table 8. Predictor Variables for The Center for Nonprofit Management Inc.

No.	**Predictor Variable**	**Value**
X_1	CFO/CL	0.971
X_2	(CFO + INT + TAX)/ INT	35.000
X_3	CFO/SALES	0.144
X_4	CFO/TA	0.442
X_5	EBIT/CFO	2.765

After using Equation 3, we obtained the values presented in Table 8. The predicted value, or Z_i, for the nonprofit equals 11.711. Next, the value obtained was entered into equation 4. Based on our calculations, The Center for Nonprofit Management Incorporated has a 99.999 percent probability of success in the following year.

EXAMPLE NO. 3 – THE CITY OF DETROIT, MICHIGAN

The audited partial financial statements of the City of Detroit, Michigan for June 30, 2012, was obtained and the information needed to calculate the predictor variables is presented in Table 9. This information is used to calculate the five predictor variables in Table 10.

Consistent with the previous examples, we calculated the value of the dependent variable, Z_i, which equals -7.496.[3] The probability of success, using the June 30, 2012, audited financial statements, for the City of Detroit, Michigan was 0.050 percent. This conclusion for the City of Detroit, Michigan fairly represents the distress the city was in that resulted in it filling bankruptcy in 2013.

Table 9. Partial Audited Financial Statements for the City of Detroit, Michigan

Audited Financial Data *(in millions)*	**Values**
Cash flow from operations (CFO)	-$40.23
Current liabilities (CL)[4]	642.11
Interest expense (INT)	126.73
Tax expense (TAX)	0.00
Net sales (SALES)	1,523.64
Total assets (TA)	606.28
Earnings before interest and tax (EBIT)[5]	1,650.37

Table 10. Predictor Variables for the City of Detroit, Michigan

No.	**Predictor Variable**	**Value**
X_1	CFO/CL	(0.063)
X_2	(CFO + INT + TAX)/ INT	0.683
X_3	CFO/SALES	(0.026)
X_4	CFO/TA	(0.066)
X_5	EBIT/CFO	(41.023)

The three above examples clearly show the versatility of our model's ability to predict the probability of success/distress of any type of organization- profit or nonprofit. The predictions in these examples turned out to be in line with the actual outcome.

SUMMARY AND CONCLUSION

Many bankruptcy prediction models have been created over the years using a mix of variables derived mostly from accrual-based accounting statements and were industry specific. The primary issue with using a model comprised of accrual-based variables is that firm management can manipulate different components of the balance sheet and income statement to make the values misleading (Wanuga 2006). Thus, firms may appear financially healthy yet unable to meet day-to-day cash flow needs of the entity, which is less likely to be hidden in the cash flow statement (Sharma 2001).

In this paper, we use a binary regression model with theoretically supported variables derived from the cash flow statement to predict firm success versus distress. Of particular interest, we examine firms representing 42 industries using firm data during and immediately following the greatest recession in United States history (Fieldhouse 2014; Lee 2014). The model, therefore, is generic in the sense that it can be used to predict the probability of success-distress of any organization as long as the three major financial statements are available. We also find that the model correctly classifies successful and distressed firms with high accuracy rate.

Unlike other success/distress models, our model can be used on many types of entities. Using three examples, we show that the model can not only predict the success/distress of for-profit entities, but we can also predict the success/distress of nonprofit organizations and government entities.

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AUTHOR BIOGRAPHIES

Dr. Bhandari worked at Bradley University between 1976 and 2017. He has taught courses in statistics, finance, and international business. He has received many awards and grants and is a former president and Program Chair of the Academy of Finance.

In 2014, **Dr. Johnson** joined the Bradley University faculty and teaches auditing and financial accounting. She has worked as a government auditor, internal auditor, and in the private industry in the areas of auditing and financial accounting. Anna enjoys conducting research on issues in the auditing work environment, professional judgment, and audit quality.

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ENDNOTES

[1] The computer program was presented in a graduate level statistic course by Dr. J. Dan Morris (2012).
[2] The formula containing the calculation for the City of Detroit, Michigan is not presented due to the unusual length of the values.
[3] This value was calculated using Net Loss of $513 plus interest and tax expense, which equals earnings before interest and tax of - $89.
[4] This value was calculated using total liabilities of $646.53 minus litigation and judgments of $4.43.
[5] This was calculated using total revenue of $1,523.64 plus an interest expense of $126.73.

APPENDIX A

Two-digit Standard Industrial Classification (SIC) Codes and Descriptions (85 Industries)(United States Department of Labor 2016, 1-2)

SIC	SIC Description	Frequency	Percent
1044	Silver Ores	1	0.571
1220	Bituminous Coal and Lignite Mining	3	1.714
1311	Crude Petroleum and Natural Gas	5	2.857
1531	Operative Builders	2	1.143
1700	Construction- Special Trade Contractors	1	0.571
2015	Poultry Slaughtering and Processing	3	1.714
2090	Miscellaneous Food Preparations and Kindred Products	1	0.571
2300	Apparel and Other Finished Products of Fabrics and Similar Materials	1	0.571
2510	Household Furniture	3	1.714
2531	Public Building and Related Furniture	2	1.143
2621	Paper Mills	2	1.143
2631	Paperboard Mills	2	1.143
2731	Books: Publishing or Publishing and Printing	2	1.143
2741	Miscellaneous Publishing	1	0.571
2750	Commercial Printing	2	1.143
2820	Plastic Material, Synthetic Resin/Rubber and Cellulose (No Glass)	3	1.714
2834	Pharmaceutical Preparation	3	1.714
2836	Biological Product (No Diagnostic Substances)	5	2.857
2860	Industrial Organic Chemicals	4	2.286
2990	Miscellaneous Products of Petroleum and Coal	1	0.571
3080	Miscellaneous Plastics Products	2	1.143
3312	Steel Works, Blast Furnaces and Rolling Mills (Coke Ovens)	1	0.571
3341	Secondary Smelting and Refining of Nonferrous Metals	1	0.571
3480	Ordinance and Accessories (No Vehicles/Guided Missiles)	1	0.571
3490	Miscellaneous Fabricated Metal Products	1	0.571
3550	Special Industry Machinery (No Metalworking Machinery)	2	1.143
3620	Electrical Industrial Apparatus	1	0.571
3661	Telephone and Telegraph Apparatus	4	2.286
3663	Radio and Television Broadcasting and Communications Equipment	2	1.143
3669	Communications Equipment, Not Elsewhere Classified	2	1.143
3674	Semiconductor and Related Devices	5	2.857
3690	Miscellaneous Electrical Machinery, Equipment and Supplies	5	2.857
3695	Magnetic and Optical Recording Media	2	1.143
3711	Motor Vehicles and Passenger Car Bodies	1	0.571
3714	Motor Vehicle Parts and Accessories	4	2.286
3720	Aircraft and Parts	1	0.571
3821	Laboratory Apparatus and Furniture	1	0.571
3826	Laboratory Analytical Instruments	1	0.571
3827	Optical Instruments and Lenses	1	0.571
3829	Measuring and Controlling Devices, Not Elsewhere Classified	3	1.714
3841	Surgical and Medical Instruments and Apparatus	1	0.571
3844	X-Ray Apparatus and Tubes and Related Irradiation Apparatus	1	0.571
3861	Photographic Equipment and Supplied	1	0.571
3910	Jewelry, Silverware and Plated Ware	1	0.571
3949	Sporting and Athletics Goods, Not Elsewhere Classified	1	0.571
4412	Deep Sea Foreign Transportation of Freight	1	0.571
4512	Air Transportation, Scheduled	1	0.571
4813	Telephone Communications (No Radiotelephone)	4	2.286
4832	Radio Broadcasting Stations	1	0.571

(Appendix continued on next page)

(Appendix continued)

4841	Cable and Other Pay Television Services	2	1.143
4888	Communications, Non-specific	2	1.143
5122	Wholesale- Drugs, Proprietaries and Druggists' Sundries	1	0.571
5160	Wholesale- Chemicals and Allied Products	1	0.571
5180	Wholesale- Beer, Wine and Distilled Alcoholic Beverage	1	0.571
5311	Retail- Department Stores	2	1.143
5621	Retail- Women's Clothing Stores	8	4.571
5700	Retail- Home Furniture, Furnishings and Equipment Stores	2	1.143
5731	Retail- Radio, TV and Electronics Stores	1	0.571
5812	Retail- Eating Places	1	0.571
5912	Retail- Drug Stores and Proprietary Stores	2	1.143
6020	Commercial Banking	2	1.143
6172	Financial Lessors	2	1.143
6200	Security and Commodity Brokers, Dealers, Exchanges and Services	1	0.571
6510	Real Estate Operators (No Developers) and Lessors	2	1.143
6531	Real Estate Agents and Managers (For Others)	1	0.571
6552	Land Subdividers and Developers (No Cemeteries)	2	1.143
6798	Real Estate Investment Trusts	3	1.714
7310	Services- Advertising	1	0.571
7370	Services- Computer Programming, Data Processing, etc.	3	1.714
7371	Services- Computer Programming Services	1	0.571
7372	Services- Prepackages Software	9	5.143
7373	Services- Computer Integrated Systems Design	1	0.571
7374	Services- Computer Processing and Data Preparation	2	1.143
7389	Services- Business Services, Not Elsewhere Classified	1	0.571
7812	Services- Motion Picture and Video Tape Production	1	0.571
7822	Services- Motion Picture and Video Tape Distribution	1	0.571
7841	Services- Video Tape Rental	2	1.143
7990	Services- Miscellaneous Amusement and Recreation	6	3.429
7996	Services- Amusement Parks	2	1.143
8000	Services- Health Services	2	1.143
8071	Services- Medial Laboratories	2	1.143
8200	Services- Educational Services	1	0.571
8731	Services- Commercial Physical and Biological Research	1	0.571
8999	Services, Not Elsewhere Classified	1	0.571
9995	Non-Operating Establishments	2	1.143