Predicting Bankruptcy After The Sarbanes-Oxley Act Using Logit Analysis

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ABSTRACT

Our study proposes firm bankruptcy prediction using logit analysis after the passage of the Sarbanes-Oxley (SOX) Act using 2008-2009 U.S. data. The results of our logit analysis show an 80% (90% with one year before bankruptcy data) prediction accuracy rate using financial and other data from the 10-K report in the post-SOX period. This prediction rate is comparable to other data mining tools. Overall, our results show that, as compared to the prediction rates documented by other bankruptcy studies before SOX, firm bankruptcy prediction rates have improved since the passage of SOX. Our findings shed light on the benefits of SOX by providing evidence that legislation makes the financial reporting more informative. This study is important for regulators to implement public policy. Investors may be interested in our findings to better assess company risk when making portfolio decisions.

Keywords: Sarbanes-Oxley Act; Bankruptcy; Logit Analysis

INTRODUCTION

The Sarbanes-Oxley Act (SOX) of 2002 was introduced to require reporting on the effectiveness of any material weaknesses in internal controls over financial reporting by a firm's top CEOs and accountants. The objective of SOX is to enhance the reliability of financial statements. Therefore, SOX will improve the quality of financial reporting and deter corporate fraud in the U.S.; however, opponents have been concerned that the costs of implementing the provisions of SOX may outweigh the benefits. This issue of costs and benefits of the SOX effect is still a controversial issue as the SEC recently excluded the implementation of SOX for small firms with sales less than 75 million (Solnik, 2010).

One major benefit of SOX is the improvement of financial reporting quality, thereby enabling investors or other decision makers to sort out good and bad companies. In this study, we examine firm bankruptcy after the passage of SOX and compare the overall prediction accuracy rates with those of general bankruptcy studies before SOX. We use logit analysis in this study because it enables us to identify the specific variables that contribute to bankruptcy prediction. Based on the logit model, we find an 80% (90% with one year before bankruptcy data) prediction accuracy rate using financial and other data from the 10-K report after SOX. This prediction rate is comparable to other data mining tools. Overall, our results show that, compared with other previous logit bankruptcy studies, firm bankruptcy prediction rates improved after the passage of SOX.

This paper adds to a growing body of research that documents the benefits of SOX. Evidence on the bankruptcy prediction accuracy is likely to be of interest to standard setters. The improved accuracy in predicting firm bankruptcy after the passage of SOX helps investors better evaluate the distress risk of companies when making portfolio decisions. In this sense, the findings of this study have implications in making investment decisions.

The next section presents the background and prior research relevant to our study, followed by a section describing our sample data and reports our empirical results, and concluding with a summary of our findings and future research avenues.

BACKGROUND AND PRIOR RESEARCH

SOX was introduced to minimize financial fraud and reestablish investor confidence after major scandals such as Enron and Worldcom at the turn of century, but after another market crash in 2008, investors doubted the true impact of SOX. The benefits of SOX are supposed to improve corporate governance mechanisms and improve the quality of financial reporting for investors. However, costs of SOX are not trivial for small firms and the SEC finally excluded small firms from the SOX implementation. SOX was fully implemented in the U.S. in 2008 for medium or large firms and our study tries to measure the benefits of SOX using the firm bankruptcy study context.

There are two types of errors (Type-I and Type-II) involved in general prediction studies like ours. Type-I error refers to false rejection error. For example, in a bankruptcy prediction study, we reject the null hypothesis that a firm is a non-bankrupt firm even though the firm is actually a bankrupt firm. This type of error will be very costly for a decision maker. A Type-II error is the opposite case. For example, we predict a firm to be a bankrupt firm, even though the firm is not a bankrupt firm. In the Type-II error case, the cost of misclassification is not as severe as in the Type-I error case. For our study, we focus on overall prediction accuracy and Type-I errors because the cost of misclassifying can be significant.

Altman (1968) originally used multiple discriminant analysis (MDA) by using five financial ratios to predict firm bankruptcy using a manufacturing sample and matching control firms. Ohlson (1980) later used a logit model that does not require any assumptions about the prior probability of the bankruptcy sample. However, as Grice and Dugan (2001) later pointed out, hold-out sample tests are potentially upwardly biased. Platt and Platt (1990) also suggested that the differences in the macro economic factors are sensitive to specific time periods. Therefore, Grice and Ingram (2001) empirically tested and reported that Altman's (1968) study using a small sample of 33 manufacturing firms and the use of an equal sample size of bankrupt and non-bankrupt firms using a sample from 1958 to 1961 reported 83.5% overall accuracy. However, Altman's model using the 1988-1991 test period showed that the overall correct classification rate dropped to 57.8%. Begley et al. (1996) also reestimated both Altman's (1968) and Ohlson's (1980) models using 1980 data and reported that Ohlson's model showed a Type-I error rate of 29.2% and a Type-II error rate of 14.9% at the cutoff point of 0.061. They suggested that both models' accuracy rates drop as they are applied in different time periods, but Ohlson's model is a preferred model because it does not require any assumptions about the prior probability of bankruptcy sample. In our study we also want to compare both models after the passage of SOX to test this issue.

Goal programming (GP) was proposed by Freed and Glover (1986) to minimize misclassifications of Type-I and Type-II errors. However, the GP approach is not practical because of computational problems around that time (Koehler and Erenguc, 1990).

Shumway (2001) proposed a simple hazard model to be better for bankruptcy prediction studies like ours, but we do not have longitudinal data to apply his model and we decided to use the traditional logit model for this study to check which variables are contributing to bankruptcy prediction.

Recently, several researchers had compared machine learning, neural networks, case-based reasoning, and statistics approaches using experiments to predict bankruptcy, but their results are not conclusive as to which methods outperform the other methods (see, Sung et al., 1999, Yip, 2006 and Peng et al., 2009, for example). Rough sets theory is also proposed because a cause-effect relationship between factors and the actual occurrence of bankruptcy is not easy (McKee, 2000), but empirical study showed 61% and 68% accuracy rates using this theory (McKee, 2003). Duffie et al. (2007) proposed a multi-period bankruptcy model would be better using large sample firms. Generally, bankruptcy prediction rates around 85% are acceptable and some data mining method prediction rates are context specific.

SAMPLE DATA, VARIABLES, AND EMPIRICAL RESULTS

In this paper, we used the data search engine DirectEDGAR (2008) to identify 35 (130 for three-year data) firms that filed bankruptcy in 2008 and 2009. Next, we collected more than double the number of matching control firms based on firm size and the two-digit industry codes that had no bankruptcy filing to emulate the real world context. We started with more than double the number of control firms, because the three years of financial data for some firms are not available and these control firms are excluded from further analyses. Our final control firms are composed of 306 firm-year observations for the three years that have available financial and other data in Form 10-K filings using DirectEDGAR and Compustat.

In selecting variables that may help predict firm bankruptcy after SOX, we included Altman et al.'s (1968) variables and Ohlson's (1980) variables because these variables have proven to be useful in bankruptcy prediction studies.

First, we run our logit model using five variables as Altman (1968) did in his study.

$$\textit{Bankruptcy (1), otherwise (0)} = \alpha_0 + \Sigma\, \beta \textit{ Altman's five ratios } (X1, \ldots\ldots, X5) + \varepsilon \tag{1}$$

X1 =Working capital divided by total assets (WCA_TA)
X2 = Retained earnings divided by total assets (RE_TA)
X3 = Earnings before interest and taxes divided by total assets (EBIT_TA)
X4 = Market value of equity divided by book value of total debt (MKV_TD)
X5 = Sales divided by total assets (SALES_TA)

The ratio of working capital to total assets (*WCA_TA*) is a proxy for firm liquidity. The working capital ratio measures the ability of a company to pay its incoming debt. The lower the working capital, the higher the possibility of being bankrupt. The ratio of retained earnings to total assets (*RE_TA*) captures the extent to which assets have been paid for by cumulative profits. Altman (1968) finds that younger firms have a higher risk of bankruptcy than older firms due to a lack of time to build up cumulative profits. Earnings before interest and taxes, scaled by total assets (*EBIT_TA*), is used to measure operating efficiency apart from any tax and leveraging factors. This is an important predictor of firm bankruptcy, given the fact that a firm's existence depends on the earning power of its assets. We use market value of equity, divided by book value of total debt (*MKV_TD*), to proxy for firm leverage. A low equity/debt ratio increases the risk of insolvency. Finally, asset turnover ratio, defined as sales divided by total assets (*SALES_TA*), is included to evaluate the firms' effectiveness in managing assets. The higher the assets turnover ratio, the better the management's capability to generate revenues.

Next, we run our model using Ohlson's (1980) nine variables.

$$\textit{Bankruptcy (1), otherwise (0)} = \alpha_0 + \Sigma\, \beta \textit{ Ohlson's nine ratios } (Y1, \ldots\ldots, Y9) + \varepsilon \tag{2}$$

Y1: Size, measured as the logarithm of total Assets (SIZE)
Y2: Total liabilities divided by total assets (TL_TA)
Y3: Working capital divided by total assets (WCA_TA)
Y4: Total current liabilities divided by total current assets (CL_CA)
Y5: Net income divided by total assets (NI_TA)
Y6: If TL_TA>**1** then OENEG=**1**; else OENEG=**0**
Y7: Funds from operations divided by total liabilities (FU_TL)
Y8: If Net Income<**0** or lag (Net Income) <**0** then INTWO=**1**; else INTWO=**0**
Y9: CHIN= (Net Income- lag (Net Income))/ [absolute (Net Income) + absolute (lag Net Income)]

As documented by Ohlson (1980), smaller firms (*SIZE*), firms with higher financial leverage (*TL_TA*), firms with current liquidity problems (lower *WCA_TA* and/or higher *CL_TA*), and firms with poorer performance measures (*NI_TA* and/or *FU_TL*) increase the likelihood of business failure.

In addition to the above bankruptcy prediction variables, we included internal control weakness, stock market return, and dividend missing variables. These variables were useful in firm bankruptcy prediction in previous studies (see, Sun, 2007; Hammersley, et al. 2008, for example). However, our sample firms near bankruptcy stage are missing most of the return data.

Table 1 shows the descriptive statistics. As shown, all variables between bankrupt firms and non-bankrupt firms are significantly different except for Size (*SIZE*), Funds from operations/Total liabilities (*FU_TL*), Changes in income/Average Income of two years (*CHGREIN*), firm's Market value of equity/Total debts (*MKV_TD*), Sales/Total assets (*SALES_TA*), and Annual market return data (*RET*). Size is not supposed to be different as we matched control firms based on total assets. Annual market return data are not significant because of a lot of missing data for bankrupt firms. As we matched based on size and industry, bankrupt firms and non-bankrupt Market value of equity/Total debts and Sales/Total assets are similar as we expected. For one-year data, the results are similar except Funds from operation/Total liabilities and Market return data are marginally significant compared with 3-year data and not reported for brevity. However, Total liabilities/Total assets > 1 ratio is not significant. In addition, Earning before interest and taxes/Total assets and Internal control weakness variables are marginally significant.

Table 1: Descriptive Statistics With Firm Year Data

Bankrupt =1						
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**	**t-stat** (1)
SIZE	130	3.036	0.670	1.067	4.251	1.88
TDEBT_TA	130	0.522	0.373	0.000	2.365	6.54***
WCA_TA	130	0.004	0.366	-2.356	0.574	-5.30***
CL_CA	130	1.325	1.917	0.139	13.667	3.46***
NI_TA	130	-0.128	0.238	-1.367	0.544	-4.99***
FU_TL	130	33.568	347.968	-52.720	3949.740	-0.70
LOSS	130	0.815	0.389	0.000	1.000	11.59***
OENEG	130	0.085	0.279	0.000	1.000	2.98**
CHGREIN_TA	130	-3.045	27.966	-198.828	110.229	-1.24
EBIT_TA	130	-0.014	0.131	-0.924	0.171	-5.49***
MKV_TD	130	42.646	410.251	0.000	4648.890	-1.35
SALES_TA	130	1.235	0.858	0.016	4.439	1.82
RE_TA	130	-0.593	1.168	-7.327	0.470	-5.04***
IC	130	0.208	0.407	0.000	1.000	4.71***
DIV	128	0.758	0.430	0.000	1.000	3.38***
RETX	28	-0.489	0.938	-2.371	1.086	-1.84
Bankrupt =0						
Variable	**N**	**Mean**	**Std Dev**	**Minimum**	**Maximum**	
SIZE	306	2.899	0.768	-0.220	5.301	
TDEBT_TA	306	0.292	0.229	0.000	1.080	
WCA_TA	306	0.186	0.215	-0.670	0.824	
CL_CA	306	0.728	0.681	0.093	9.785	
NI_TA	306	-0.006	0.219	-2.188	0.589	
FU_TL	306	83.021	1119.380	-78.358	19433.310	
LOSS	306	0.314	0.465	0.000	1.000	
OENEG	306	0.010	0.099	0.000	1.000	
CHGREIN_TA	304	0.004	0.068	-0.248	0.365	
EBIT_TA	306	0.071	0.182	-2.160	0.889	
MKV_TD	306	386.955	4421.000	0.002	75722.150	
SALES_TA	306	1.081	0.668	0.080	3.137	
RE_TA	306	-0.013	0.919	-11.439	1.558	
IC	306	0.033	0.178	0.000	1.000	
DIV	306	0.598	0.491	0.000	1.000	
RETX	212	-0.153	0.644	-4.071	1.608	

(1) t-value for testing mean differences between bankrupt and non-bankrupt firms
*: $p < 0.10$
**: $p < 0.05$
***: $p < 0.001$

Variable Descriptions:

Size	= the log of total assets
TDEBT_TA	= total debt divided by total assets (Ohlson 1980 ratio)
WCA_TA	= working capital divided by total assets (Altman 1968 ratio and Ohlson 1980 ratio)

CL_CA	= total current liabilities divided by total current assets (Ohlson 1980 ratio)
NI_TA	= net income divided by total assets (Ohlson 1980 ratio)
FU_TL	= funds from operations divided by total liabilities (Ohlson 1980 ratio)
LOSS	= if net income<**0** or lag (net income) <**0** then INTWO=**1**; else INTWO=**0** (Ohlson 1980 dummy variable)
OENEG	= if TL/TA>**1** then OENEG=**1**; else OENEG=**0** (Ohlson 1980 dummy variable)
CHGREIN	= (net income- lag (net income))/ [absolute (net income) + absolute (lag net income)] (Ohlson 1980 ratio)
EBIT_TA	= earnings before interest and taxes divided by total assets (Altman 1968 ratio)
MKV_TD	= market value of equity divided by book value of total debt (Altman 1968 ratio)
SALES_TA	= sales divided by total assets (Altman 1968 ratio)
RE_TA	= retained earnings divided by total assets (Altman 1968 ratio)
IC	= If internal control weaknesses are mentioned in 10-K then IC=1; 0 otherwise
DIV	= If the dividend is missing then 1; 0 otherwise
RETX	= the firm's annual average market return

Table 2 presents our results using Altman's (1968) five ratios. This model is significant as maximum rescaled R-square is 22%, Likelihood Chi-Square is 73.61, and Wald's Chi-Square is 42.93 and significant at less than .001. The overall prediction rate is 75% (one-year data prediction rate is 83% and not reported here) and this rate is comparable with that of a similar data mining bankruptcy study by Kwak et al. (2012). Not surprisingly, we find that the coefficient on *MKV_TD* (market value of equity divided by total debts) is not significant given that as shown in Table 1. *MKV_TD* is not significantly different between bankrupt and non-bankrupt firms. The result indicates market value of a firm is not important for bankruptcy prediction.

Table 2: Logit Regression Analysis Using Altman's Five Predictor Variables With 3-Year Data (N = 436)

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-1.1077	0.2231	24.6579	<.0001
EBIT_TA	-2.4221	1.1390	4.5220	0.0335
MKV_TD	-0.00081	0.000835	0.9408	0.3321
SALES_TA	0.5399	0.1640	10.8338	0.0010
WCA_TA	-2.6565	0.6335	17.5862	<.0001
RE_TA	-0.3393	0.1724	3.8724	0.0491

Likelihood Chi-Square	73.61
Wald's Chi-Square	42.93
Max-rescaled R-Square	0.2206
Overall prediction rate	75%

Variables are defined in Table 1.

Table 3 presents logit analysis results with Ohlson's (1980) nine-variable model. Overall, this model is significant as the maximum rescaled R-square is 37%, Likelihood Chi-Square is 131.35, and Wald's Chi-Square is 86.84 and significant at less than .001. The overall prediction rate is 77% (one-year prediction rate is 84% and not reported here). As expected, the prediction rate of Ohlson's (1980) model is 2% higher than Altman's (1968) model. However, variables CL_CA (current liabilities divided by current assets), FU_TL (funds from operation divided by total liabilities), and OENEG (if TL/TA>1 then OENEG=1; else OENEG=0) are not significant in predicting business failure.

Table 3: Logit Analysis Using Ohlson's Nine Predictor Variables With 3-Year Data (N=434)

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-3.3930	0.7249	21.9061	<.0001
SIZE	0.3397	0.1809	3.5248	0.0605
TDEBT_TA	1.2728	0.6242	4.1578	0.0414
WCA_TA	-1.8096	0.8832	4.1983	0.0405
CL_CA	0.0137	0.1571	0.0076	0.9306
NI_TA	1.2142	0.7390	2.6999	0.1004
FU_TL	0.00007	0.00013	0.2761	0.5993
LOSS	2.1535	0.3222	44.676	<.0001
OENEG	0.4756	0.8848	0.2889	0.5909
CHGREIN	-0.0199	0.00910	4.7929	0.0286

Likelihood Chi-Square	131.35
Wald's Chi-Square	86.84
Max-rescaled R-Square	0.3704
Overall prediction rate	77%

Variables are defined in Table 1.

Table 4 presents the combined variable model and maximum-scaled R-square as 45.38%. Likelihood ratio and Wald test show 167.36 and 93.91, respectively, and significant at less than .001. The overall prediction rate is 80% (one-year prediction rate is 90% and not reported here) for this model. We conclude the logit model performs better consistently as firms approach near bankruptcy stage. Size is not significant as we expected. Similar to the results presented in each individual model, we find that CL_CA (current liabilities divided by current assets), FU_TL (funds from operation divided by total liabilities), OENEG (if TL/TA>1 then OENEG=1; else OENEG=0), and MKV_TD (Market value of equity divided by total debts) are not significant at the conventional levels.

Table 5 reports the combined model with other variables proven to be significant in previous bankruptcy prediction studies. Maximum-rescaled R-square is 57.6% and Likelihood ratio and Wald test are 84.16 and 33.00, respectively, and significant at the .01 level. The overall prediction rate is 73.9% (one-year prediction rate is 81.7%). This is not surprising because we lose a lot of data entered in the analysis. Interestingly, the internal control variable is significant at the .05 level and the dividend missing variable is marginally significant. However, the market return variable is not significant because of missing values of near-bankrupt firms. Each variable contributing to the overall model is consistent with previous model, except that *NI_TA* (Net income divided by total assets) and *EBIT_TA* (Earnings before interest and taxes divided by total assets) variables are not significant.

Most of the bankruptcy predictors are strongly correlated with each other. The high correlation raises the problem of multicollinearity. Although multicollinearity does not decrease the predictive power of the model as a whole, the regression coefficients may be biased and, therefore, we are unable to determine the attributes that are associated with bankruptcy. To address the issue of multicollinearity, we perform a principal component factor analysis. The factor analysis reduces a set of observable variables to a small number of factors. The extracted common factors reflect the underlying dimensions of the economic determinants of firm bankruptcy. Following the Kaiser (1960) rule, we retain all factors with eigenvalues greater than one. This process gives us three factors. Table 6 Panel A shows that the three factors explain 91 percent of the total variance in the data with the combined Altman (1968) and Ohlson (1980) variables. Then the reduced three factors are rotated using an oblique rotation. The oblique rotation allows the factors to be correlated with each other. In our case, the correlations among the three factors are less than 0.1, suggesting the extracted three factors are essentially orthogonal.

Table 4: Combination Of Altman's And Ohlson's Predictor Variables With 3-Year Data (N=434)

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-4.1255	0.8076	26.0972	<.0001
SIZE	0.2507	0.2200	1.2983	0.2545
TDEBT_TA	2.0512	0.7157	8.2144	0.0042
WCA_TA	-1.9557	0.9582	4.1660	0.0412
CL_CA	0.0164	0.1545	0.0112	0.9156
NI_TA	3.4068	0.9847	11.9695	0.0005
FU_TL	0.0057	0.007	0.6670	0.4141
LOSS	2.0999	0.3523	35.5363	<.0001
OENEG	0.2250	0.9080	0.0614	0.8043
CHGREIN	-0.0218	0.0098	4.8856	0.0271
EBIT_TA	-3.7374	1.4830	6.3510	0.0117
MKV_TD	-0.0033	0.0052	0.4124	0.5208
SALES_TA	0.8328	0.2230	13.9498	0.0002
RE_TA	-0.2400	0.1679	2.0442	0.1528

Likelihood ratio Chi-Square	167.36
Wald's Chi-Square	93.91
Max-rescaled R-Square	0.4538
Overall prediction rate	80%

Variables are defined in Table 1.

To interpret the factors, we examine the association between the combined Altman (1968) and Ohlson (1980) variables and each factor. We link each factor with those variables when the coefficient of each factor loading is greater than 0.4 in absolute value and is significantly different from zero at conventional levels. Table 6 Panel B presents the association between each factor and the resulting variables. The first factor explains 47% of total variation in the four variables, with loadings for LOSS, NI_TA, EBIT_TA, and RE_TA of -0.55, 0.70, 0.86, 0.79, and 0.74, respectively. Variables WCA_TA, TDEBT_TA, and CL_TA load strongly on the second factor, with loadings of 0.91, -0.61, and -0.69, respectively. The third factor has two variables, FU_TL and MKV_TD, with loadings of 0.88 and 0.75, respectively. Based on the characteristics of the variables that are related to each factor, we conclude that factor 1 captures the notion of firm profitability. The higher value of factor 1 implies higher net income and hence higher retained earnings. Factor 2, on the other hand, seems to capture the notion of firm liquidity. The higher value of factor 2 suggests a larger margin of safety where the company is able to cover its debts. Finally, factor 3 appears to capture firm financial leverage.

Table 5:Combination Of Altman's And Ohlson's Models With Other Control Variables

Parameter	**Estimate**	**Standard Error**	**Wald Chi-Square**	**Pr > ChiSq**
Intercept	-11.0940	2.6711	17.2496	<.0001
SIZE	1.6419	0.6691	6.0221	0.0141
TDEBT_TA	4.2971	1.6079	7.1418	0.0075
WCA_TA	-5.1853	2.4744	4.3915	0.0361
CL_CA	-0.2247	0.2926	0.5902	0.4424
NI_TA	2.0735	3.1013	0.4470	0.5037
FU_TL	0.0157	0.0418	0.1407	0.7076
LOSS	2.0575	0.8103	6.4483	0.0111
OENEG	-0.6038	2.1665	0.0777	0.7805
CHGREIN	0.1017	0.0610	2.7830	0.0953
EBIT_TA	0.1062	3.7459	0.0008	0.9774
MKV_TD	-0.0082	0.0313	0.0695	0.7921
SALES_TA	0.6763	0.6462	1.0952	0.2953
RE_TA	0.5144	0.7566	0.4623	0.4966
RETX	0.3489	0.4341	0.6463	0.4215
IC	2.8552	1.1766	5.8883	0.0152
DIV	1.1998	0.6923	3.0040	0.0831

Likelihood ratio Chi-Square	84.16
Wald's Chi-Square	33.00
Max-rescaled R-Square	0.5761
Overall prediction rate	73.9%

Variables are defined in Table 1.

Table 6 Panel C shows the regression results using the extracted common factors. This model is significant as maximum rescaled R-square is 31.87%. The likelihood Chi-Square is 83.75 and Wald's Chi-Square is 51.62. We find that the coefficients on factor 1 and factor 2 are significantly negative, suggesting that firms with poorer performances and firms with liquidity problems have a higher incidence of bankruptcy. However, factor 3 is insignificant in predicting business failure. The overall prediction rate is 75.8% with three-year data and 83.4% with one-year data. In short, the results presented in Table 6 Panel C suggest the extracted factors affect the accuracy of bankruptcy prediction.

Table 6: Factor Analysis: Combination Of Altman's And Ohlson's Models

Panel A: Component Factors

Factor	Eigenvalue	Percentage Explained	Cumulative Percentage
1	3.47	0.47	0.47
2	1.98	0.27	0.74
3	1.25	0.17	0.91

Panel B: Component Loading Analysis

Factor	Component Loading
Factor 1 (Profit)	
LOSS	-0.55
NI_TA	0.86
EBIT_TA	0.79
RE_TA	0.74
Factor 2 (Liquidity)	
WCA_TA	0.91
TDEBT_TA	-0.61
CL_TA	-0.69
Factor 3 (Leverage)	
FU_TL	0.88
MKV_TD	0.75

Panel C: Association Between Extracted Factors And The Likelihood Of Bankruptcy

Parameter	Estimate	Standard Error	Wald Chi-Square	Pr > ChiSq
Intercept	-1.7302	0.1977	76.607	<.0001
Factor1	-0.5818	0.1582	13.52	0.0002
Factor 2	-0.5826	0.2032	8.2252	0.0041
Factor3	-0.00005	0.00014	0.1246	0.7241

Likelihood ratio Chi-Square	83.75
Wald's Chi-Square	51.62
Max-rescaled R-Square	0.3187
Overall prediction rate	75.8%

Variables are defined in Table 1.

Finally, we conduct a supplementary factor analysis with the combined model and other control variables, such as internal control weakness, stock market return, and dividends. We find qualitatively similar results as Table 6. Untabulated results show that the loadings of these control variables are less than 0.20 in absolute value, suggesting that the control variables have insignificant associations with the extracted factors. Taken together, our factor analysis provides consistent results on the determinants in predicting firm bankruptcy based on past financial data.

SUMMARY AND CONCLUSIONS

Our findings will justify the benefits of SOX and it will be important for regulators for implementing public policy. Investors may be interested in our findings to better assess the distress risk of companies when they make portfolio decisions. It is still a controversial issue that benefits of SOX will improve the quality of corporate financial reporting and enhance investor confidence, but costs of compliance are not trivial. In this paper, we used logit analysis to predict bankruptcy after SOX using 2008-2009 data. The results of our logit analysis in bankruptcy prediction study show 80% accuracy rate (90% for one year before bankruptcy data) and is comparable with other data mining approaches.

Our paper has several limitations. We only have a small sample of bankrupt firms and most market return data are missing. Another limitation is that bankrupt firms and non-bankrupt firms are heterogeneous and their actual probabilities of bankruptcy are non-observable (Baixauli and Modica-Milo, 2010). We may need other variables to improve the overall prediction accuracy and minimize the type-I error rate.

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