HARVARD UNIVERSITY

JOHN F. KENNEDY SCHOOL OF GOVERNMENT

Faculty Research Working Papers Series

Assessing Financial Vulnerability in the Nonprofit Sector

Elizabeth K. Keating, Mary Fischer,

Teresa P. Gordon, Janet Greenlee

January 2005

RWP05-002

Assessing Financial Vulnerability in the Nonprofit Sector[*]

Elizabeth K. Keating[Ψ], Assistant Professor of Public Policy, Kennedy School of Government, Harvard University, Cambridge, Massachusetts 02138.

Mary Fischer, Professor of Accounting, University of Texas at Tyler, College of Business and Technology, 3900 University Blvd., Tyler, Texas 75701.

Teresa P. Gordon, Professor of Accounting, University of Idaho, College of Business & Economics, P. O. Box 443161, Moscow, Idaho 83844-3161.

Janet Greenlee, Associate Professor of Accounting, University of Dayton, 300 College Park, Dayton, Ohio 45469-224

---

[*] July 2004. We acknowledge the helpful comments of the participants of the 2003 ARNOVA conference and the 2003 Midyear Meeting of the Government and Nonprofit Section of the American Accounting Association. The data used for this paper is available from the National Center for Charitable Statistics and US Census Bureau.

[Ψ] Corresponding author. Tel. (617) 495-9856. Fax (617) 495-8963. Email: elizabeth_keating@harvard.edu

Assessing Financial Vulnerability in the Nonprofit Sector

Abstract

Effective nonprofit governance relies upon understanding an organization's financial condition and vulnerabilities. However, financial vulnerability of nonprofit organizations is a relatively new area of study. In this paper, we compare two models used to forecast bankruptcy in the corporate sector (Altman 1968 and Ohlson 1980) with the model used by nonprofit researchers (Tuckman and Chang 1991). We find that the Ohlson model has higher explanatory power than either Tuckman and Chang's or Altman's in predicting four different measures of financial vulnerability. However, we show that none of the models, individually or combined, are effective in predicting financial distress. We then propose a more comprehensive model of financial vulnerability by adding two new variables to represent reliance on commercial-type activities to generate revenues and endowment sufficiency. We find that this model outperforms Ohlson's model and performs substantially better in explaining and predicting financial vulnerability. Hence, the expanded model can be used as a guide for understanding the drivers of financial vulnerability and for identifying more effective proxies for nonprofit sector financial distress for use in future research.

Keywords: financial vulnerability, financial distress, bankruptcy prediction, nonprofit

JEL descriptors: L31 (nonprofit institutions); M41 (accounting)

1. Introduction

In the past few years, a series of financial scandals have shaken several large nonprofits, including Planet Aid Canada (Cribb 2002), the NAACP, United Way, Upsala College, and the Nature Conservancy (Gibelman, Gelman and Pollack 1997, Stephens 2004). These and other high profile cases – along with the growing visibility of the sector – have generated calls throughout North America for strengthening nonprofit governance (for example, see Boudreau 2003, Strom 2003). In the US, several states, notably New York, have proposed that the Sarbanes-Oxley Act[1] be applied more broadly to nonprofit organizations, while the US Senate Finance Committee has held hearings on proposed legislation that would substantially increase in regulation and alter board governance practices (Office of New York State Attorney General 2003, US Senate Finance Committee 2004).

Indeed, an essential governance role is financial oversight and accountability. Board members are responsible not only for mitigating fraud but also for ensuring that organizations have sufficient financial resources to fulfill its mission in the present and the future. Hence, effective nonprofit governance relies upon understanding an organization's financial condition and vulnerabilities. The ability to predict which organizations may become financially vulnerable is also important to government regulatory agencies when setting accountability and disclosure policies, external accountants when determining the risk inherent in an audit, foundations when distributing and monitoring grants, and management during the strategic planning process.

Our sample period (1998-2000) is of potential interest due to the onset of adverse economic conditions. The stock boom ended soon after the turn of the century with the bursting of the "dot.com" bubble in 2000, sending technology stocks and the market as a whole downward. While economic indicators and the stock market continued to decline in 2000, the economy had not yet been impacted by the unforeseen and catastrophic conditions that followed the September

11, 2001 terrorist attacks and exacerbated a growing recession. In addition to entity-specific factors, the financial health of nonprofit organizations is impacted by economic conditions through several mechanisms. First, individual giving is affected by both personal income and employment rates, which tend to decline during recessions. Corporate donations also decline when corporate profits decline. Second, stock and bond market declines impact individual, foundation, and corporate giving as well as endowment earnings. In particular, foundation giving declines since the required payout ratio is based on lower portfolio values and this reduces funds available for distribution. Third, government contracts and grants expand and contract in accordance with economic conditions as well as political ramifications of the changing composition of legislatures and executive officers and attitudes toward deficit spending at the federal level. Nonprofit organizations began to feel the impact of these declines in 2000 as revenues were stretched to meet continuing high demand for services.

Prior research in this area has been constrained by small samples dominated by large nonprofit organizations, limited financial data availability, use of less powerful and biased regression techniques, and a potentially weak explanatory model. Greenlee and Trussel (2000) were the first to develop a prediction model for the nonprofit sector by applying methods that have been used extensively in the for-profit sector. Their model, like later efforts (Hager 2001; Trussel 2002; and Trussel and Greenlee 2004), used accounting ratios initially developed by Tuckman and Chang (1991). We look to the for-profit literature for other potentially useful independent variables, specifically to Altman (1968) and Ohlson (1980). Both of these models have been used extensively in the business sector to predict bankruptcy and financial distress. We compare the usefulness of the Tuckman and Chang variables to those from Altman and Ohlson using a discrete hazard rate model rather than a single period logit model.

We find that the Ohlson model has higher explanatory power than either Tuckman and Chang's or Altman's in predicting four different measures of financial vulnerability. However, we show that none of the models are effective in classifying organizations at risk. We then propose a more comprehensive model of financial vulnerability. We find that the proposed model outperforms Ohlson's model and does substantially better in explaining and predicting financial vulnerability. Hence, the revised model should be used a guide to understanding the drivers of financial distress and for identifying more effective proxies for financial vulnerability to be used in future research.

The paper continues as follows: Section II describes the prior literature, contrasting the work in the nonprofit field with that in the corporate arena. Section III outlines our research methodology, while Section IV discusses our sample selection. In Section V, we present the descriptive statistics and regression results. We present an alternative model in Section VI. The final section summarizes and concludes the paper.

2. Prior Literature

The For-Profit Perspective

Corporate bankruptcy prediction has been a popular area of research since the late 1960s. This area of research has relied primarily on accounting measures such as profitability, cash flow, and leverage ratios as predictor variables. Of the early studies, Altman (1968) became the most influential. In that paper, he developed a Z-Score based on five variables that had the highest predictive power in a multivariate discriminant analysis model (MDA). The probability of bankruptcy increases as the Z-Score decreases, and Altman reports that a cutoff value of 2.675 minimizes the total Type I and Type II classification errors. The Z-Score is still widely used by both academics and practitioners.

The next generation of default studies, including Santomero and Vinso (1977), Ohlson (1980), and Zmijewski (1984), employed multinomial choice techniques, such as maximum-likelihood logit and probit. Of the multinomial choice-based studies, Ohlson's (1980) one-year prediction model has been widely cited and used. Researchers often rely on an O-Score calculated using Ohlson's original coefficients from Model 1 as a proxy for financial distress. The popularity of the Altman (1968) and Ohlson (1980) models is reflected in the frequent use of the two models as empirical proxies for bankruptcy risk in accounting research. A recent study by Begley, Ming and Watts (1996) compares the predictive accuracy of the two models using both the original coefficients and estimates based on more recent data. They find that the magnitudes (and some of the signs) of several parameter values have significantly shifted for both models. Hillegeist, Keating, Cram and Lundstedt (2004) find that the Ohlson model using updated coefficients has greater predictive power than the original Ohlson and Altman models as well as the Altman model with updated coefficients.[2]

The Nonprofit Perspective

Taken as a whole, the nonprofit sector in the United States is equivalent to a major industry that employs seven percent of all workers and grosses $665 billion in annual revenues (Independent Sector 2002). The million-plus nonprofit organizations engage in a wide range of activities ranging from small museums and cemetery organizations to major hospitals and universities. These organizations are neither governmental agencies nor businesses operated to earn a return for their owners. They exist to provide a public benefit (normally the purview of government) within a private organizational context. They do not operate to earn a profit, and no ownership interest can ever be redeemed, transferred or sold (Salamon 1999). However, nonprofit entities are similar to business organizations in that they compete for scarce capital resources (whether in the form of loans, donations or government contracts) and lack the coercive taxing power of government.

While bankruptcy prediction has long been a popular research topic in the for-profit sector, only a few studies have focused on nonprofits. There are two primary reasons for this.

First, few nonprofits ever declare bankruptcy; to a large extent, they either merge with other nonprofits or simply "disappear" (Hager, Galaskiewicz and Bielefeld 1996).[3] Thus, using "bankruptcy" as the independent variable excludes a substantial group of nonprofits that may be at risk financially. Second, until fairly recently, it was only possible to examine a small number of nonprofits, since nonprofit databases were largely unavailable (Gordon, Greenlee and Nitterhouse 1999).

In 1991, Tuckman and Chang posited that a nonprofit was financially vulnerable if it were "likely to cut back its service offerings immediately when it experiences a financial shock" such as the loss of a significant source of funds or a general economic downturn (p. 445). They identified four accounting ratios that could be used to indicate financial vulnerability: few revenue sources, insufficient net assets, low administrative costs, and low income from operations. Tuckman and Chang then obtained a random sample of 4,730 nonprofit organizations' 1983 Form 990 tax returns from the US Internal Revenue Service (IRS), computed the four ratios and divided the results into quintiles. They defined as "severely at risk" any nonprofit with all four ratios in the lowest quintile. A nonprofit with only one ratio in the bottom quintile was defined as "at risk". Tuckman and Chang made no attempt to see if these variables could actually be used to predict the *future* financial distress of these organizations.

Greenlee and Trussel (2000) were the first to use Tuckman and Chang's ratios to develop a model to predict financial distress in the nonprofit sector. Because of the lack of data on nonprofit bankruptcies, they defined as "financially vulnerable" any nonprofit organization that saw an overall decline in program expenses during a three-year period. Using the recently available Form 990 database provided by the National Center for Charitable Statistics (NCCS) and a methodology initially developed by Altman (1968), they examined data from the 1992–1995 Form 990s of 6,795 nonprofits. They found a significant relationship between financial distress and three of Tuckman and Chang's variables.

Trussel and Greenlee (2004) expanded this study in five ways. First, they included size in the model, since smaller organizations may be more vulnerable to financial distress than larger ones. Second, they controlled for nonprofit sub-sector, since different types of nonprofits may be impacted differently by changes in the economy. Third, they defined “financial distress” as a “significant” decrease in net assets over a three-year period. Fourth, they tested the resulting models for robustness by applying them to different time periods. Finally, they developed a way to rate the financial vulnerability of nonprofits. Their composite model was robust and was, with some accuracy, able to predict financial distress. Significant relationships were found between financial distress and two Tuckman and Chang measures and between financial distress and organizational size.

Trussel (2002) used a broader data set to predict financial vulnerability. The NCCS Core Files includes smaller organizations but fewer data fields. The final sample included 94,002 charities for the period 1997-1999 and financial distress was defined as a 20 percent reduction in net assets over a three-year period. Two of the Tuckman and Chang variables could not be computed since the necessary information was not coded by the Internal Revenue Service (equity ratio and administrative cost ratio). Trussel replaced the equity ratio with a debt ratio (total liabilities divided by total assets) and added a size variable. Due to the expanded data set, nonprofit sub-sector control variables were more detailed than possible in previous studies. All the variables were statistically significant, and the predictive ability exceeded that of a naïve model.

Hager (2001) examined the ability of the Tuckman and Chang ratios to predict the actual demise of arts organizations. He found that predictive ability varied within the sector: the Tuckman and Chang measures could be used to predict the closure of some, but not all, arts organizations.

Comparison of the Prediction Models

The *Tuckman and Chang* model has been the only one used, so far, to predict financial distress in the nonprofit sector. Their model uses four variables: equity ratio (total equity/total revenue), revenue concentration index, administrative cost ratio (administrative expenses/total revenue), and surplus margin (net income/total revenues). To measure the revenue concentration, we divide the revenue sources into three categories: donations (total contributions and net special event revenue), earned income (program service revenue, dues and assessments, profits from sale of inventory and other revenue), and investment income (interest, dividends, net rental expenses, other investment income, and realized gains/losses on sales of securities or other assets). The three revenue sources (identified as *i* below) are combined as follows:

$$\text{RCI} \quad = \quad \sum\left(\frac{\text{Revenue}_i}{\text{Total Revenue}}\right)^2 \qquad (1)$$

The *Altman* model has been used for over four decades to predict corporate bankruptcy and has been the foundation for at least one commercially sold model. The model relies on five variables: working capital-to-total assets (WC/TA), retained earnings-to-total assets (RE/TA), earnings before interest and tax-to-total assets (EBIT/TA), market value of equity-to-total liabilities (MVE/TL), and sales-to-total assets (S/TA). The variable selection appears relatively intuitive, with measures representing liquidity, solvency, profitability, leverage, and asset turnover, respectively. In contrast to Tuckman and Chang, the variables in the Altman model are scaled by total assets rather than total revenues. To implement the model in the nonprofit setting, several adjustments to the model are required. First, the nonprofit equivalent for retained earnings is “net assets” but, unlike retained earnings, net assets represent the entirety of the capital structure. Similarly, sales are referred to as total revenues. Most importantly, MVE/TL is excluded due to the lack of information on the market valuation of the firms. If the book value of equity were used as a surrogate for market value, the resulting variable would be highly correlated with the solvency variable.[4]

The *Ohlson* model is less parsimonious and uses multiple variables for certain factors. For liquidity, his model includes working capital-to-total assets (WC/TA) as well as current liabilities-to-current assets (CL/CA). Profitability is represented by three variables: net income-to-total assets (NI/TA); a discrete variable (INTWO) that is one if Net Income was negative for the last two years, zero otherwise; and a scaled change in net income (CHIN). Solvency is captured by total liabilities-to-total assets (TL/TA) and a discrete variable (NAFail) that is one if net assets are negative, zero otherwise.[5] Ohlson's model does not include a measure of asset turnover but does include size and cash flow variables. SIZE is the log of total assets scaled by the GDP deflator, while FFO/TL is funds from operations divided by total liabilities. To estimate this model, we modified several variables. Due to the lack of historical data, INTWO was changed to being one if the prior year's net income was negative. As no cash flow statement is provided in Form 990, we estimate funds from operations using income before interest and depreciation, commonly known as EBITDA.[6]

3. Research Methodology

Discrete Hazard Rate Regression Model

As a regression technique, we use a discrete hazard model used by Shumway (2001) and Hillegeist et al. (2004) rather than the more common single-period logit approach. Our rationale for choosing the discrete hazard model is based on Allison (1984), Beck, Katz and Tucker (1998), and Shumway (2001). The discrete hazard model estimates the probability of bankruptcy, *p,* using the following function form:

$$\log\left(\frac{p_{it}}{1-p_{it}}\right) = \alpha(t) + X_{it}\beta \qquad (2)$$

where α*(t)* is a time-varying and/or industry-specific variable that captures the underlying baseline hazard rate. In contrast to the discrete hazard model, the ordinary logit model has the following form:

$$\log\left(\frac{p_i}{1-p_i}\right) = \alpha + X_i\beta \qquad (3)$$

The discrete hazard maximum likelihood estimator differs from ordinary logit in two important ways. First, as the time-script *t* indicates, the hazard rate model includes multiple observations for the same firm, *i*. In logit models, researchers generally select the year prior to bankruptcy for bankrupt firms, and just one observation for non-bankrupt firms. This process introduces a sample selection bias. Relying on a single observation per firm neglects most firm-years during which the firm was at risk of bankruptcy but remained solvent. Shumway (2001) demonstrates that this sample selection procedure generates biased and inconsistent coefficient estimates.

Second, the logit models may be misspecified by not including variables that capture the systematic changes in the underlying or baseline risk of bankruptcy, α*(t)*. By including a baseline hazard rate, the discrete hazard model addresses the issue of dependence arising from a fluctuating systematic hazard rate. For example, the underlying bankruptcy risk may be higher in a certain industry or during an economic recession. Optimally, this is done by including the system-level variables, such as macro-economic factors, that cause the temporal or industry-specific dependence in the data. We model the baseline hazard in the nonprofit sector by using both industry and time dummies.[7]

The discrete hazard rate model can suffer from a problem of dependence due to the inclusion of multiple observations from the same firm. This intertemporal firm dependence can result in understated standard errors. Similar to Hillegeist et al. (2004), we use Huber-White standard errors to address this problem (Huber 1967, White 1980). The Huber-White correction is conservative in that it may bias the *t*-statistics downward. Thus, our statistical methodology should yield unbiased and consistent coefficient estimates while preventing overstated t-statistics.

Test Design

Our research design is chosen to determine which variables best explain the likelihood of financial distress. Unlike prior research that relied on a single measure of financial distress, we use four different dichotomous measures of dramatic adverse shifts in financial health, all of which relate to the ability of a nonprofit organization to carry out its mission. Due to the limited number of years in our sample, we are unable to test a more gradual decline in financial health as was used in Gilbert, Menon and Schwartz (1990), Trussel (2002), Trussel and Greenlee (2004).

1. *Insolvency risk.* Insolvency exists when total liabilities are greater than total assets. An insolvent organization is one that is unable to pay its debts as they become due, which would necessarily impact its ability to provide services. To measure insolvency, we develop an indicator variable that is one when a firm has negative net assets or zero when net assets are zero or positive.

2. *Financial disruption.* A potential early warning sign of future insolvency is a sharp drop in net assets. We define a financially disrupted nonprofit as one with a 25 percent or greater decline in net assets during a 12-month period.[8]

3. *Funding disruption.* An organization with a significant loss of funding will, at some point, be forced to reduce or eliminate services. We define an organization that is experiencing a funding disruption as one with a 25 percent or greater decline in total revenues during a 12-month period.

4. *Program disruption.* An organization that reduces the funds it allocates to program expenses is necessarily disrupting or reducing its mission-based services. Greenlee and Trussel (2000) defined as financially vulnerable any nonprofit with any decline in program expenses over a three-year period. Due to data limitations, we rely on a shorter window. Accordingly, we define a programmatically-disrupted organization as one with a 25 percent or more reduction in allocations to program expenses during a 12-month period.

We estimate discrete hazard models for each of the four financial vulnerability proxies using the Altman, Ohlson, and Tuckman and Chang predictor variables. Many prior studies, such as Begley, Ming and Watts (1996) examine classification errors to determine the effectiveness of a model in predicting an event. Prediction accuracy is assessed by comparing the total Type I and II error rates for each alternative specification. An overall statistic of the percentage of correct classifications is determined based on the relative frequency of successes and failures. In keeping with that literature, we present classification error results. As a default, we use a cutoff probability of 0.50 to classify the observations but conducted tests of robustness using other probabilities.[9]

Other researchers (e.g., Hillegeist et al. 2004) argue that relative and incremental information content tests are preferable to analysis of classification error rates. When the same number of variables is employed, one can compare the results of discrete hazard models using the Wald χ^2 statistic and the Pseudo-R^2. However, the Ohlson model does not contain the same number of regressors as the Altman and Tuckman and Chang models. Hence, we use a non-linear version of the Vuong (1989) test that determines statistically whether one set of variables has a significantly greater likelihood statistic than a second set.[10] These tests show whether some of the explanatory variables from the less powerful models provide significant incremental information beyond that of the most powerful model.[11]

4. Sample Selection

The annual Internal Revenue Service Form 990 tax filing is the principal disclosure mechanism of nonprofit organizations in the United States. The sample data used in our analysis originates from these annual filings. The data is repackaged and disseminated to academic researchers by the Urban Institute's National Center on Charitable Statistics (NCCS). Unlike earlier research (such as Trussel 2002) which had to rely on the particular data fields the IRS chose to encode for its own purposes, this more recent dataset, known as the *digitized dataset*, includes essentially all the variables contained on Form 990 or Form 990EZ.

While this dataset is the most comprehensive dataset for the nonprofit sector, it is not without limitations. Churches are not required to file. Of the remaining nonprofits, only those with over $25,000 in annual revenues are required to file Form 990s annually with the IRS. As discussed in Keating and Frumkin (2003), Form 990 deviates, in a number of important regards, from audited financial statements prepared in accordance with generally accepted accounting principles (GAAP). For example, Form 990 can be prepared on a cash basis and from unaudited data. Certain expenses like cost of goods sold must be reported as contra-revenues. Revenues exclude unrealized investment gains and losses and the value of certain donated services that are recognized under GAAP. Thus there are systematic differences between GAAP-based revenues and expenses as compared to those reported on Form 990. In contrast, balance sheet totals are more likely to be in agreement (see Froelich and Knoepfle 1996, Gantz 1999, Froelich, Knoepfle and Pollak 2000, and Fischer, Gordon and Kraut 2002). In addition, the returns are often filed late and prone to errors. Moore and Williams (1998) estimate that over half of the filings with errors failed to include Schedule A, about one-fifth were not signed, and one-tenth indicated the wrong tax year.[12]

The sample is drawn from the NCCS dataset on 501(c)(3) tax-exempt organizations filing Form 990s in the 1998 to 2000 period. The final sample totals 290,579 nonprofit organizations drawn from the 1999 and 2000 dataset.[13] In addition, 8,918 firm year observations were dropped because they covered a reporting period that was shorter or longer than 12 months. As we are interested in explaining the first instance of financial distress, any particular observation is removed if the firm had already experienced this form of distress in the prior year. Hence, the number of observations included in a regression varies with the dependent variable of interest.

5. Results

Descriptive Statistics

As Table 1, Panel A, indicates, our sample is composed of 290,579 firm-year observations covering 1999 and 2000. During this period, the annual rate of insolvency was 7.1 percent, just half as high as the likelihood of experiencing a drop of 25 percent or more in net assets (14.4 percent). A comparable percentage decline in total revenues was almost as frequent at 12.7 percent, while a 25 percent drop in program expenses was 9.4 percent. As a comparison, the corporate bankruptcy rate for the comparable period was 2.1 percent (Hillegeist et al. 2004).

Table 1

Financial vulnerability, however measured, differs considerably across nonprofit subsectors. Human service organizations exhibited the highest rate of insolvency at 10.5 percent, with health-related groups experiencing the next highest insolvency rate at 7.6 percent. Surprisingly, these two groups did not experience the highest rates of financial, funding and program disruption risk. In fact, human services posted among the lowest rates for disruption risks of any subgroup. Educational and other nonprofit organizations experienced low rates of insolvency at 3.5 percent and 3.8 percent, respectively. The “all other category” comprises a diverse group of entities including environmental organizations, public policy, and federated fundraising. This sub-sector had the highest percentage of firms that experienced funding and program disruptions (18.5 percent and 12.7 percent, respectively).

Table 2 provides descriptive statistics on the full sample. The statistics suggest that the sample is somewhat skewed, based on the difference between the mean and the median results. The median organization has a relatively concentrated funding mix (RCI), has only modest levels of leverage (TL/TA) at seven percent, operates with an annual surplus (NI/TR) that average six percent, and spends eight percent of its revenues on administrative costs (AE/TR).

<u>Table 2</u>

Surprisingly, the correlation between the four failure variables is relatively low; the risk of insolvency is only correlated 0.14, -0.04, and 0.01 with financial, funding and program disruption risks, respectively (Table 3). The highest correlation among the dependent variables is 0.33 between funding and program disruption risks (TRDrop and PEDrop). The correlation between the dependent and the independent variables is also remarkably low. The revenue concentration index (RCI) is the Tuckman and Chang variable with the highest correlations: 0.09 with insolvency risk and 0.08 with financial disruption. All other correlations between Tuckman and Chang variables and the dependent variables are 0.03 or less. The four Altman predictive variables have correlations of -0.17 to 0.05 with the four dependent variables. The Ohlson variables exhibit a rather uneven relation with the financial vulnerability measures. INTWO is correlated 0.25 with insolvency risk and 0.16 with financial disruption, while SIZE is correlated -0.22 with financial disruption risk (NADrop). Change in net income (CHIN) is correlated -0.18 and -0.28 with financial and funding disruptions, respectively. Finally, SIZE and CHIN show the strongest relation with program disruption risk at -0.07 and 0.08, respectively.

<u>Table 3</u>

Regression and Test Results

Insolvency risk.

The models presented in Table 4, Panel A, attempt to identify organizations that have more liabilities than assets and are, therefore, technically insolvent. The effectiveness of the three models is dramatically different. The Tuckman and Chang model has virtually no explanatory power despite three of the four variables being statistically significant and in the expected direction. In contrast, the Altman and Ohlson models have higher explanatory power in terms of both pseudo R^2 and log likelihoods. This finding is not surprising, given that both models contain financial leverage measures (NA/TA and TL/TA) that are not included among the Tuckman and Chang variables.[14] The superior explanatory power of the Ohlson model is due to the significance of the size variable and the two prior profitability variables (INTWO and CHIN). In other words, the Ohlson model finds that insolvency is more likely when a firm is small (SIZE), experienced a loss in the prior year (INTWO) and a decline in net income from the prior year (CHIN). Interestingly, The Altman and Ohlson models are much better at predicting nonprofit insolvency with R^2 of 0.14 and 0.34, respectively, than they are in estimating corporate bankruptcy.[15]

<u>Table 4</u>

We then conduct tests of the models' ability to predict insolvency correctly. In Table 4, Panel B, we report the success in classifying the observations using a cutoff probability of 0.50.[16] We find none of the models are effective at predicting failure. In fact, the naïve model that simply predicts that no firms will become insolvent performs as well or better than the Tuckman and Chang and Altman models.[17] The Ohlson model performs modestly better in classifying firms (98.37 percent correct to 98.34 percent for the other models). While the prediction classification errors are practically indistinguishable for the insolvency risk models, the series of Vuong (1989) tests indicate that the Ohlson model outperforms the Altman and Tuckman and Chang models not only individually but also collectively (Table 4, Panel C).

Financial disruption risk.

Organizations that are not technically insolvent may suffer a sharp decline in net assets that would take them closer to insolvency. The models of financial disruption risk are presented in Table 5, Panel A. For the Tuckman and Chang model, three variables (RCI, NI/TR and AE/TR) are significant but only two have the expected sign and the model overall yields a Pseudo-R^2 of just 0.04.[18] The Altman model performs more weakly with a Pseudo-R^2 of 0.01 even though all four variables were at least marginally significant. In contrast to the first two models, the Ohlson model yields much greater explanatory power with a Pseudo-R^2 of 0.18. All variables except WC/TA have the predicted sign and SIZE, NI/TA, INTWO, NAFail, and CHIN are all significantly related to a sharp drop in net assets. Notably absent from the significant variables is the measure of financial leverage (TL/TA) that was significant in predicting insolvency.

Table 5

As the regression statistics indicate, the Ohlson model performs substantially better than the other models individually or combined when Vuong tests are conducted (Table 5, Panel C). Despite its superior explanatory power, the Ohlson model actually classifies more firms incorrectly than the naïve model. As seen in Table 5, Panel B, the naïve model is marginally more effective in classifying firm years correctly than the three empirical models. However, this assumes that the cost of a classification error is the same for false positive and false negatives. The Ohlson model produces a different pattern of errors than the naïve and other prediction models. Specifically, it is less likely to falsely classify a firm as healthy when it is financially distressed, while it is more likely to falsely classify a financially robust firm as unhealthy.

Funding disruption risk.

These models attempt to predict a 25 percent decline in revenues, our third proxy for financial vulnerability. Results are presented in Table 6. Consistent with findings of Greenlee and Trussel (2000), the revenue concentration index is positively related to the risk of severe funding drops. Overall, the Tuckman and Chang model has higher explanatory power in predicting a funding disruption with a Pseudo-R^2 of 0.08 than it had in foreshadowing insolvency (Table 4) or a sharp drop in net assets (Table 5) even though only one of the four variables carried the predicted sign. The Altman model again has little explanatory power (Pseudo-R^2 of 0.02) with just one of the four explanatory variables being both significant and in the predicted direction.

The Ohlson model has the highest explanatory power. The same five variables that were significant for predicting financial disruption risk (SIZE, NI/TA, INTWO, NAFail, and CHIN) are at least marginally significant for predicting funding disruption, although the coefficients on the SIZE, NI/TA and NAFail variables carry the wrong sign. The Ohlson model continues to have higher explanatory power than the Tuckman and Chang and Altman models combined as shown in Table 6, Panel C. The Tuckman and Chang model exhibits higher explanatory power than the Altman model (Table 6, Panel C) and has a slightly better ability to classify firm-years as compared to the other models (Table 6, Panel B).

<u>Table 6</u>

Program disruption risk.

The fourth set of models attempts to identify organizations that experience a 25 percent decline in program services (Table 7). The explanatory power of all three models is remarkably low with Pseudo-R^2 of between 0.01 and 0.02. These weak results are consistent with the findings of Greenlee and Trussel (2000). The Tuckman and Chang model has two variables that are significant and carry the predicted sign as compared to just one for the Altman model. As was the case with the financial and funding disruption risk proxies, Tuckman and Chang variables have more explanatory power than the Altman variables (see Panel C in Tables 5, 6 and 7). The Tuckman and Chang model also performs marginally better classifying entities as vulnerable (Table 7, Panel B). However, the Ohlson variables continue to outperform the other two models both individually and combined (Table 7, Panel C). Size, profitability (INTWO and CHIN) and leverage are the only variables from the Ohlson model that are significant in the program disruption model with the coefficient on CHIN being positive rather than the expected negative sign (Table 7, Panel A).

<u>Table 7</u>

6. Toward A New Model of Financial Vulnerability

The low predictive and explanatory ability of models derived from the for-profit business sector may be a result of the highly diverse nonprofit sector and unique characteristics of the nonprofit form. Bowman (2002) argues that characteristics unique to nonprofit organizations affect their decision to borrow. The unique characteristics he lists include the lack of owners, existence of donor-restrictions on assets, the ability to sell tax-exempt bonds, and the fact that nonprofit entities cannot be forced into involuntary bankruptcy. He found that endowments are an important part of the financial structure of many large nonprofit firms and that it was necessary to isolate the confounding effect of their endowments to understand the financing decisions these organizations make with respect to operating assets and liabilities. Since institutions with large endowments are concentrated in education (colleges and universities) and health care (hospitals), financial vulnerability models that control for industry segment may be picking up more fundamental underlying differences in financial structure.

In this section, we explore whether a new model may have higher explanatory and predictive power. We consider two large categories of variables that may be significantly related to financial distress – systematic and firm-specific. Systematic risk includes macroeconomic, regional and industry factors that affect revenues (such as donations, investment income, and program service revenue) as well as the demand for services. Proxies for this include inflation, gross domestic and state product, the level of corporate earnings, stock and bond returns, and government funding of certain programs. These and other macroeconomic factors may be impounded in the control variables for year used in this study since the markets and other economic factors were declining during 2000 as compared to the prosperity of 1998 and 1999. The other systematic risk factor that we control uses industry groupings based on the newer North American Industry Classification System (NAICS).

The firm-specific risk is essentially a fundamental analysis of a nonprofit firm in the spirit of Lev and Thiagarajan (1993) and Arbarbanell and Bushee (1997). These papers examine the relation between specific accounting-based fundamental signals, on one hand, and earnings and stock returns, on the other. Our analysis starts with the fundamental signals from the Tuckman and Chang, Altman, and Ohlson models.[19]

We then supplement the variables from these three models with two others that nonprofit literature has found to be important in evaluating financial health. These are reliance on commercial revenues (Frumkin and Keating 2003) and endowment sufficiency (Bowman 2002). For the *reliance on commercial revenues* measure, we use commercial revenue as a share of total revenue, where commercial revenues are composed of proceeds from sales of goods as well as program service fees and charges generally paid by clients, insurance companies or some government agencies. Consistent with Frumkin and Keating (2003), we expect that a firm will be less likely to experience financial distress if it relies more heavily on commercial rather than donative revenues since contributions are often non-recurring and sensitive to changes in economic and political conditions. For *endowment sufficiency*, we use the ratio of investment portfolio to total assets. We expect that organizations experience less funding and hence program disruption if they can rely more heavily on an endowment and its associated investment income.[20]

Therefore, both the reliance on commercial revenues (COMREV/TR) and endowment sufficiency (INV/TA) variables are expected to carry a negative coefficient in the models.

Table 8 portrays our results. The new variables added explanatory power to all four prediction models. Their impact is most clear with respect to the funding and program disruption risk proxies for financial vulnerability. For these two models, the coefficients for COMREV/TR and INV/TA were significant and carried the predicted sign. For insolvency risk and financial disruption risk (a sharp decline in net assets), the picture was less clear. The existence of an investment portfolio appears to increase the risk of financial disruption as indicated by the significant positive coefficient on INV/TA in that model. The level of commercial revenues appears to increase the risk of insolvency as indicated by the significant positive coefficient on COMREV/TR in the insolvency risk model. COMREV/TR is not significant in the financial disruption risk model and INV/TA was not significant in the insolvency risk model.

<u>Table 8</u>

In Panel C of Table 8, we compare the performance of our new models to the best performing benchmark model (Ohlson). We find that the expanded models outperform the best benchmark model for each of the four financial vulnerability proxies. For the insolvency and financial risk models, the increase in Psuedo-R^2 is quite modest. However, in the case of funding disruption risk, our new model produces a Psuedo-R^2 of 0.19 in contrast to the Pseudo-R^2 of 0.13 for the Ohlson model. In addition, the new model is able to correctly classify 88.62 percent of the sample (Table 9, Panel B) in contrast to the 87.45 percent correctly identified by the Ohlson model (Table 6, Panel B). In the case of program disruption risk, the new model has twice the explanatory power of the benchmark model. The Vuong tests indicate that the overall explanatory power of the expanded models is substantially higher than the best single model (Ohlson) for all four proxies (Table 8, Panel C).

7. Summary, Limitations, and Conclusions

This study assesses the effectiveness of three existing financial distress models in predicting technical insolvency (liabilities greater than assets) or sharp changes in the financial health of nonprofit organizations. Due to the increased availability of a broader range of financial variables, we are able to compute some ratios that could, in the past, be examined for only a small subset of primarily large tax-exempt organizations. On the other hand, the available data does not permit us to examine more than a one-year lag or predict financial vulnerability more than one year in advance. The brevity of the time series also makes it difficult to meaningfully consider macroeconomic variables that may contribute to systematic risk or firm-specific multi-year patterns, such as small but accumulating declines in revenue.

We find that the Ohlson (1980) model consistently outperforms another commonly used for-profit model reported in Altman (1968) as well as a prediction model based on Tuckman and Chang (1991) that has been used in nonprofit research. These results are robust to the choice of proxy for financial vulnerability.

While the existing prediction models provide insights into some indicators of future financial vulnerability, they are not very effective in distinguishing the particular firms that will experience distress. Therefore, researchers and practitioners are not encouraged to use any of these models for purposes of default or bankruptcy prediction. The expanded model that is proposed here, however, offers significant improvements in explanatory power, particularly when funding disruption is the measure of financial vulnerability. The addition of the two variables (reliance on commercial revenues and endowment sufficiency) improves the relative explanatory power for every proxy examined.

Predicting when nonprofit organizations will need to substantially cut program expenses seems to be the most difficult challenge. All models showed little explanatory power and most of the variables useful for predicting other measurers of financial vulnerability were either not significant or had the opposite sign when used to predict program cuts. This is possibly due to the desire on the part of nonprofit managers and boards to protect program services at all costs and find ways to fund mission-related activities even in the face of declining revenues or net assets. More work in this area would appear to be warranted since board members and donors are most interested in whether an organization will be able to continue to provide services.

With the availability of more complete financial datasets on nonprofit organizations, future researchers may be able to use a longer data series to develop a more effective model for predicting financial distress. Ideally, such a model would examine overall economic indicators and industry-specific factors as well as a more robust set of firm idiosyncratic variables that may be leading indicators of financial trouble. The specific variables selected for use in earlier models was at least partially determined by the financial data available at the time. With more complete financial data becoming available, there may be other variables unique to nonprofit organizations that would improve models originally designed for the for-profit sector. One potential way to identify such variables would be to examine the accounting, financial and economic factors that are considered when auditors issue going concern opinions or when rating agencies lower a nonprofit's bond rating.

Currently, nonprofit governing boards may be uncertain about the financial health of their organizations despite having access to reams of detailed financial data. Since there is no single bottom line ("profits") to guide decisions, proper governance of a nonprofit organization can be complex. The fruits of financial vulnerability research could be very helpful. Coefficients from a validated prediction model would enable regulators, foundations, auditors, audit committees and others to determine whether a nonprofit organization was at risk of financial distress. Regulatory agencies might use the aggregate information in setting public policy. Foundations could evaluate both potential and current grantees. A score from the model might help auditors assess risk and therefore the extent of necessary audit procedures. For trustees, a “not at risk” score might alleviate concerns while an “at risk” score could help identify potential areas of risk and guide responsible governance.

Endnotes

1. Two provisions of the US Sarbanes-Oxley Act apply to all corporate entities, regardless of tax status (BoardSource and Independent Sector 2003).
2. They also find that an option-pricing model based on Black and Scholes (1973) and Merton (1973) has higher predictive power than the original or updated Altman and Ohlson models. We are unable to use this approach as the model relies on market values and volatilities, information that is not available for nonprofit organizations.
3. Further, under the U.S. federal bankruptcy code, a nonprofit cannot be forced into involuntary liquidation or reorganization (11 U.S.C.A. § 303 (a)). Most states, however, permit nonprofits to dissolve either voluntarily or by judicial order for a variety of reasons, including abandonment of the activity of the organization. Hager et al (1996) found that Minnesotan nonprofits dissolved voluntarily because they were either unable or unwilling to carry out the activities of the organization.
4. Altman's RE/TA is replaced by NA/TA (net assets divided by total assets). The book value of equity = NA and TA minus NA equals total liabilities (TL). Thus NA/TA and NA/TL would be highly (but not perfectly) correlated.
5. Ohlson called this second solvency variable OENEG, indicating that the variable equals one when owners' equity is negative. Since this variable is identical to our NAFail risk of insolvency variable, we have renamed it. This independent variable is dropped when risk of insolvency is the proxy for financial vulnerability.
6. For for-profit entities, EBITDA stands for earnings before interest, (income) taxes, depreciation and amortization. Income taxes are not relevant for tax-exempt entities and amortization on Form 990 is combined with depreciation expense. Depreciation and amortization are excluded since they do not represent cash outflows.

7. Shumway used the natural log of firm trading age; Hillegeist et al. used the used the bankruptcy rate in the past 12 months. We are unable to use these alternatives since we do not have sufficient data.
8. Trussel and Greenlee (2004) used both 20 percent and 50 percent declines in net assets as proxies for this variable and Greenlee and Trussel (2000) used any decline in program expenses as a proxy for program disruption. For simplicity, we use a 25 percent decline for all three financial disruption proxies.
9. This analysis will be found in the Panel B section of Tables 4 through 8.
10. We thank Donald Cram for providing us with the SAS code to conduct a Vuong test using results from two logistic regressions.
11. This analysis will be found in the Panel C section of Tables 4 through 8.
12. The first two problems do not impact this study but the results might be affected through the control variables used for tax year. The dummy variables for year are also imprecise since the Form 990 filing year is denoted as the year during which the fiscal period *begins*. For example, returns dated 1999 may actually cover a substantial portion of 2000 and only a few months from 1999.
13. The 1998 dataset is used only to develop lagged variables to estimate the 1999 prediction model.
14. Since NA/TA = (1 – TL/TA), these two leverage variables are measuring the same phenomenon as shown by the 1.00 correlation in Table 2.
15. Hillegeist et al. (2004) report R^2 of 0.07 and 0.11 for the Altman and Ohlson models for the 1979-1997 sample period.
16. We conducted robustness checks using cutoff values ranging from 0.1 to 0.9. The high rate of misclassification persists under these different assumptions with the results for cutoffs of 0.25 and 0.75 being nearly identical to those using a cutoff value of 0.5.

17. Trussel (2002) also conducted extensive sensitivity tests using different cutoff probabilities and prior probabilities. He also reports that both the naïve model and a modified Tuckman and Chang model have similarly high misclassification rates under most assumptions.

18. The $\chi 2$ statistic and p-values are 2,616.40 and 0.00, respectively, which is comparable to the explanatory power of Trussel (2002). Trussel does not report Pseudo-R^2.

19. Only one version of the leverage variables (Altman's NA/TA) is included in each model since Ohlson's TL/TA = (1 – NA/TA).

20. Endowments, strictly speaking, would equal permanently restricted net assets. However, many organizations have quasi-endowments that are not donor restricted. We use the investment portfolio as a proxy for the total of funds functioning as an endowment.

References

Allison, P., 1984. *Event History Analysis.* Sage Publications, Inc., Newbury Park, California.

Altman, E., 1968. Ratios, discriminant analysis, and the prediction of corporate bankruptcy. *Journal of Finance*, 23(4), 589-609.

Arbarbanell, J., Bushee. B., 1997. Fundamental analysis, future earnings, and stock prices. *Journal of Accounting Research*, 35(1), 1-24.

Beck, N., Katz, J., Tucker, R., 1998. Taking time seriously: Time-series-cross section analysis with a binary dependent variable. *American Journal of Political Science*, 42(4), 1260-88.

Begley, J., Ming, J., Watts, R., 1996. Bankruptcy classification errors in the 1980s: An empirical analysis of Altman's and Ohlson's models. *Review of Accounting Studies* 1, 267-84.

Black, F., Scholes, M., 1973. The pricing of options and corporate liabilities. *Journal of Political Economy* 81(3), 637-54.

BoardSource and Independent Sector, 2003. The Sarbanes-Oxley act and implications for nonprofit organizations. Accessed 7/13/04 at http://www.independentsector.org/issues/sarbanesoxley.html.

Boudreau, J., 2003. Non-profit directors under new scrutiny. San Jose Mercury News, June 27.

Bowman, W., 2002. The uniqueness of nonprofit finance and the decision to borrow. *Nonprofit Management & Leadership* 12(3), 293-311.

Cribb, R., 2002. Planet Aid claimed $350,000 in losses from 1998 to 2000. *The Toronto Star*. April 26, A01.

Fischer, M., Gordon, T., Kraut, M., 2002. An examination of differences between financial information provided in IRS Form 990 and audited financial statement data of U.S. private colleges and universities. *Academy of Accounting and Financial Studies Journal* 6(1), 87-104.

Froelich, K., Knoepfle, T., 1996. Internal Revenue Service 990 data: Fact or fiction? *Nonprofit and Voluntary Sector Quarterly* 25, 40-52.

Froelich, K., Knoepfle, T., Pollak, T. 2000. Financial measures in nonprofit organization research: Comparing IRS 990 returns and audited financial statement data. *Nonprofit and Voluntary Sector Quarterly* 29(2), 232-54.

Frumkin, P., Keating, E., 2003. The Risks and Rewards of Nonprofit Revenue Concentration. Hauser Center, Harvard University Working Paper.

Gantz, M. 1999. Who do you trust? Comparing data on skilled-nursing facilities from the Internal Revenue Service and Health Care Financing Administration, *Nonprofit and Voluntary Sector Quarterly,* 28(4), 476-90.

Gibelman, M., Gelman, S., Pollack, D., 1997. The credibility of nonprofit boards: A view from the 1990s and beyond, *Administration in Social Work* 21(2), 21-41.

Gilbert, L., Menon, K., Schwartz, K., 1990. Predicting bankruptcy for firms in financial distress. *Journal of Business Finance and Accounting* 14(1), 161-71.

Gordon, T., Greenlee, J., Nitterhouse, D., 1999. Tax-exempt organization financial data: Availability and limitations. *Accounting Horizons* 13(2), 113-28.

Greenlee, J., Trussel, J., 2000. Estimating the financial vulnerability of charitable organizations. *Nonprofit Management and Leadership* 11(2), 199-210.

Hager, M., 2001. Financial vulnerability among arts organizations: A test of the Tuckman-Chang measures. *Nonprofit and Voluntary Sector Quarterly* 30(2), 376-92.

Hager, M., Galaskiewicz, J., Bielefeld, W., 1996. Tales from the grave: organizations' account of their own demise. *The American Behavioral Scientist* 39(8), 975-94.

Hillegeist, S., Keating, E., Cram, D., Lundstedt, K., 2004. Assessing the probability of bankruptcy. *Review of Accounting Studies* 9(1), 5-34.

Huber, P., 1967. The behavior of maximum likelihood estimates under non-standard conditions. In Proceedings of the Fifth Berkeley Symposium in Mathematical Statistics and Probability, University of California Press 1, Berkeley, CA, 221-33.

Independent Sector, 2002. *The New Nonprofit Almanac and Desk Reference*. Jossey-Bass. (Key facts also available at http://www.independentsector.org).

Keating, E., Frumkin, P., 2003. Reengineering nonprofit financial accountability: Toward a more reliable foundation for regulation. *Public Administration Review* 63(1), 3-15.

Lev, B., Thiagarajan, R., 1993. Fundamental information analysis. *Journal of Accounting Research* 31(2), 190-215.

Merton, R., 1973. Theory of rational option pricing. *Bell Journal of Economics* 4(1), 141-83.

Moore, J., Williams, G., 1998. A sampling of common errors on Forms 990. *Chronicle of Philanthropy*, December 17, 1998.

Office of New York State Attorney General, 2003. Attorney General Spitzer's proposed reforms to state corporate accountability laws. Press Release, March 12.

Ohlson, J., 1980. Financial ratios and the probabilistic prediction of bankruptcy. *Journal of Accounting Research* 18 (1), 109-31.

Salamon, L., 1999. *America's Nonprofit Sector: A Primer*. 2nd edition. New York: Foundation Center.

Santomero, A., Vinso, J., 1977. Estimating the probability of failure for commercial banks and the banking system. *Journal of Banking and Finance* 1(2/3), 185-206.

Shumway, T., 2001. Forecasting bankruptcy more accurately: A simple hazard rate model. *Journal of Business* 74(1), 101-24.

Stephens, J. 2004. Nature Conservancy Retools Board to 'Tighten' Oversight, *Washington Post*, March 4, A21.

Strom, S., 2003. Fees and trustees: Paying the keepers of the cash. *The New York Times*, July 16.

Trussel, J., 2002. Revisiting the prediction of financial vulnerability. *Nonprofit Management and Leadership* 13(1), 17-31.

Trussel, J., Greenlee, J., 2004.. A financial rating system for nonprofit organizations, *Research in Government and Nonprofit Accounting.* 11, 105-28.

Tuckman, H., Chang, C., 1991. A methodology for measuring the financial vulnerability of charitable nonprofit organizations. *Nonprofit and Voluntary Sector Quarterly* 20(4), 445-60.

US Senate Finance Committee, 2004. Tax exempt governance proposals: Staff discussion draft. Accessed 7/13/04 at: http://www.senate.gov/~finance/hearings/testimony/2004test/062204stfdis.pdf.

Vuong, Q., 1989. Likelihood ratio tests for model selection and non-nested hypotheses. *Econometrica* 57(2), 307-33.

White. H., 1980. A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity. *Econometrica* 48(4), 817-38.

Zmijewski, M., 1984. Methodological issues related to the estimation of financial distress prediction models. *Journal of Accounting Research* 22(Supplement), 59-86.

TABLE 1
Sample Description

Panel A: Year-By-Year Patterns in Financial Vulnerability

Year	Number of Firms	Number of NAFail	% Firms	Number of NADrop	% Firms	Number of TRDrop	% Firms	Number of PEDrop	% Firms
1999	137,080	9,711	7.08%	20,299	14.81%	17,368	12.67%	12,893	9.41%
2000	153,499	10,871	7.08%	21,667	14.12%	19,456	12.68%	14,355	9.35%
Total	290,579	20,582	7.08%	41,966	14.44%	36,824	12.67%	27,248	9.38%

Panel B: Industry Patterns in Financial Vulnerabilty

Industry	Number of Firms	Number of NAFail	% Firms	Number of NADrop	% Firms	Number of TRDrop	% Firms	Number of PEDrop	% Firms
Arts	28,320	1,670	5.90%	4,576	16.16%	4,337	15.31%	3,082	10.88%
Education	44,912	1,591	3.54%	6,391	14.23%	5,900	13.14%	4,137	9.21%
Health	47,870	3,613	7.55%	6,666	13.93%	5,424	11.33%	4,662	9.74%
Human Services	105,730	11,086	10.49%	14,796	13.99%	9,905	9.37%	7,498	7.09%
Religious	13,972	719	5.15%	2,500	17.89%	2,066	14.79%	1,527	10.93%
Other	49,775	1,903	3.82%	7,037	14.14%	9,192	18.47%	6,342	12.74%
Total	290,579	20,582	7.08%	41,966	14.44%	36,824	12.67%	27,248	9.38%

NAFail, i.e. insolvency risk, represents an excess of liabilities over assets (negative net assets)

NADrop, i.e. financial disruption risk, represents a drop of 25% or more in net assets in twelve months

TRDrop, i.e. funding disruption risk, represents a drop of 25% or more in total revenues in twelve months

PEDrop, i.e. program disruption risk, represents a drop of 25% or more in program expenses in twelve month

TABLE 2
Descriptive Statistics

Based on 290,579 firm-years

Variable	Mean	Std Dev	Median	Minimum	Maximum
NAFail	0.07	0.25	0.00	0.00	1.00
NADrop	0.14	0.35	0.00	0.00	1.00
TRDrop	0.13	0.33	0.00	0.00	1.00
PEDrop	0.09	0.29	0.00	0.00	1.00
NA/TR	1.99	30.06	0.61	-1.19	18.15
RCI	0.79	0.19	0.85	0.38	1.00
NI/TR	0.09	2.61	0.06	-1.00	0.95
AE/TR	0.13	0.93	0.08	0.00	0.88
WC/TA	0.39	3.02	0.41	-1.05	1.00
NA/TA	0.60	4.61	0.93	-1.97	1.00
EBIT/TA	0.00	3.50	0.05	-2.52	1.00
TR/TA	4.18	47.24	1.11	0.05	43.79
Size	8.10	2.27	8.05	3.07	13.96
TL/TA	0.40	4.61	0.07	0.00	2.97
CL/CA	1.64	223.63	0.03	0.00	8.98
NI/TA	0.01	3.49	0.05	-2.47	1.00
FFO/TL	36.32	5,158.62	-28.41	-190.00	0.01
INTWO	0.15	0.36	0.00	0.00	1.00
CHIN	-0.02	0.71	-0.01	-1.00	1.00

NAFail, insolvency risk, coded 1 if liabilities are greater than assets, 0 otherwise.
NADrop, financial disruption risk, coded 1 if drop in net assets ≥ 25% in 12 months, 0 otherwise
TRDrop, funding disruption risk, coded 1 if drop in total revenues ≥ 25% in 12 months, 0 otherwise
PEDrop, program disruption risk, coded 1 if drop program expenses ≥ 25% in 12 months, 0 otherwise
NA/TR is net assets divided by total revenues
RCI is the revenue concentration index defined as $\sum\left(\frac{\text{Revenue}_i}{\text{Total Revenue}}\right)^2$
NI/TR is net income divided by total revenues
AE/TR is administrative expenses divided by total revenues
WC/TA is working capital divided by total assets.
NA/TA is net assets divided by total assets.
EBIT/TA is earnings before interest and taxes divided by total assets.
TR/TA is total revenue divided by total assets
SIZE is the ln(Total Assets/GDP price level index).
TL/TA is total liabilities divided by total assets.
CL/CA is current liabilities divided by current assets.
NI/TA is net income divided by total assets.
FFO/TL is pre-tax income plus depreciation and amortization divided by total liabilities.
INTWO is one if Net Income was negative for the last year, zero otherwise.
CHIN is $(NI_t - NI_{t-1})/(|NI_t|+|NI_{t-1}|)$ is the scaled change in net income.

TABLE 3
Pearson Correlation Matrix

Based on 290,658 firm-years
Correlations greater than .20 in absolute magnitude are in bold

Variable	NAFail	NADrop	TRDrop	PEDrop	NA/TR	RCI	NI/TR	AE/TR	WC/TA	NA/TA	EBIT/TA	TR/TA	Size	TL/TA	CL/CA	NI/TA	FFO/TL	INTWO
Proxies for financial vulnerability:																		
NAFail	1.00																	
NADrop	0.14	1.00																
TRDrop	-0.04	0.11	1.00															
PEDrop	0.01	0.06	**0.33**	1.00														
Tuckman & Chang variables:																		
NA/TR	-0.03	-0.02	0.00	0.01	1.00													
RCI	0.09	0.08	0.00	0.00	-0.01	1.00												
NI/TR	-0.03	-0.01	0.03	-0.02	**-0.63**	-0.01	1.00											
AE/TR	0.01	0.00	-0.01	0.01	0.14	-0.01	**-0.52**	1.00										
Altman variables:																		
WC/TA	-0.13	-0.01	0.00	0.00	0.00	0.00	0.00	0.00	1.00									
NA/TA	-0.17	-0.04	0.01	-0.01	0.01	-0.02	0.00	0.00	**0.68**	1.00								
EBIT/TA	-0.06	-0.02	0.02	-0.02	0.00	-0.01	0.01	-0.01	0.16	0.15	1.00							
TR/TA	0.05	0.04	0.00	0.01	-0.01	0.04	0.00	0.00	-0.10	-0.14	-0.06	1.00						
Ohlson (additional) variables:																		
SIZE	-0.02	**-0.22**	0.01	-0.07	0.04	-0.14	0.01	0.01	0.00	0.05	0.05	-0.14	1.00					
TL/TA	0.17	0.04	-0.01	0.01	-0.01	0.02	0.00	0.00	**-0.68**	**-1.00**	**-0.15**	0.14	-0.05	1.00				
CL/CA	0.02	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.01	-0.01	0.00	0.00	0.00	0.04	1.00			
NI/TA	-0.05	-0.02	0.02	-0.02	0.00	0.00	0.02	-0.01	0.15	0.14	**1.00**	-0.06	0.05	**-0.14**	0.00	1.00		
FFO/TL	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	1.00	
INTWO	**0.25**	0.16	-0.02	0.02	0.00	0.04	-0.05	0.03	-0.03	-0.03	-0.05	0.01	0.01	0.03	0.01	-0.05	-0.01	1.00
CHIN	0.01	-0.18	**-0.28**	0.08	0.00	0.00	-0.04	0.02	-0.02	-0.03	-0.08	0.03	-0.07	0.03	0.00	-0.08	-0.01	0.01

All correlations that are 0.01 or greater are significant at the 1% level.

TABLE 4
Risk of Insolvency

Panel A: Discrete Hazard Regressions

	Predicted Sign	Tuckman & Chang Model	Altman Model	Ohlson Model#
Constant		-4.98	-2.11***	-3.26***
NA/TR	-	-0.26*		
RCI	+	1.30***		
NI/TR	-	-0.16***		
AE/TR	-	0.18		
WC/TA	-		0.29*	0.06
NA/TA	-		-3.33***	
EBIT/TA	-		-0.01	
TR/TA	-		0.00	
SIZE	-			-0.45***
TL/TA	+			4.00***
CL/CA	+			0.00
NI/TA	-			-0.01
FFO/TL	-			0.0
INTWO	+			2.02***
CHIN	-			-1.70***
Log Likelihood		-21,688	-19,588	-15,120
Pseudo-R^2		0.05	0.14	0.34

Insolvency risk represents negative net assets (liabilities in excess of assets)

Regression using the discrete hazard model with 270,346 firm-year observations and Huber-White standard errors to control for firm dependence.

All regressions include industry and year as controls (coefficients not shown)

Panel B: Classification Errors

	Tuckman & Chang	Altman	Ohlson	Naïve
% of False Failures	0.01%	0.00%	0.09%	0.00%
% of False Successes	100.00%	99.96%	92.99%	100.00%
% Correct Classification	98.33%	98.34%	98.37%	98.34%

Panel B uses 0.5 as the cut-off probability to classify the errors

Panel C: Relative Explanatory Power using Vuong (1989)

Comparison	z-statistic
Tuckman & Chang vs. Altman	-5.1***
Tuckman & Chang vs. Ohlson	-15.3***
Altman vs.Ohlson	-33.4***
Tuckman & Chang and Altman vs. Ohlson	-28.9***

z-statistics resulting from Vuong Test (1989). Positive/(negative) values indicate that the first/(second) group of variables explains significantly more of the variance

NAFail is omitted from the Ohlson model since it is the dependent variable

*** (**) [*] significant at the 1% (5%) [10%] level (two-sided test)

TABLE 5
Financial Disruption Risk

Panel A: Discrete Hazard Regressions

	Predicted Sign	Tuckman & Chang Model	Altman Model	Ohlson Model
Constant		-2.29***	-1.75***	0.77***
NA/TR	-	-0.13		
RCI	+	-1.08***		
NI/TR	-	-0.46***		
AE/TR	-	-0.41***		
WC/TA	-		0.15*	0.02**
NA/TA	-		-0.15*	
EBIT/TA	-		-0.00*	
TR/TA	-		0.00***	
SIZE	-			-0.39***
TL/TA	+			0.00
CL/CA	+			0.00
NI/TA	-			-0.01**
FFO/TL	-			0.00
INTWO	+			0.98***
NAFail	+			1.20***
CHIN	-			-1.13***
Log Likelihood		-104,652	-107,464	-89,784
Pseudo-R^2		0.04	0.01	0.18

Financial disruption risk represents a 25% or more decline in net assets

Regression using the discrete hazard model with 276,052 firm-year observations and Huber-White standard errors to control for firm dependence.

Panel B: Classification Errors

	Tuckman & Chang	Altman	Ohlson	Naïve
% of False Failures	0.09%	0.11%	1.47%	0.00%
% of False Successes	99.82%	99.56%	91.05%	100.00%
% Correct Classification	86.53%	86.55%	86.51%	86.58%

Panel B uses 0.5 as the cut-off probability to classify the errors

Panel C: Relative Explanatory Power using Vuong (1989)

Comparison	z-statistic
Tuckman & Chang vs. Altman	13.7***
Tuckman & Chang vs. Ohlson	-62.6***
Altman vs.Ohlson	-88.1***
Tuckman & Chang and Altman vs. Ohlson	-62.5***

z-statistics resulting from Vuong Test (1989). Positive/(negative) values indicate that the first/(second) group of variables explains significantly more of the variance

All regressions include industry and year as controls (coefficients not shown)

*** (**) [*] significant at the 1% (5%) [10%] level (two-sided test)

TABLE 6
Funding Disruption Risk

Panel A: Discrete Hazard Regressions

	Predicted Sign	Tuckman & Chang Model	Altman Model	Ohlson Model
Constant		-2.23***	-1.50***	-1.99***
NA/TR	-	0.00		
RCI	+	0.20***		
NI/TR	-	2.22***		
AE/TR	-	0.43		
WC/TA	-		-0.08***	-0.02*
NA/TA	-		0.07***	
EBIT/TA	-		0.13***	
TR/TA	-		0.00	
SIZE	-			0.02***
TL/TA	+			-0.00*
CL/CA	+			0.00
NI/TA	-			0.01*
FFO/TL	-			0.00
INTWO	+			0.06***
NAFail	+			-0.24***
CHIN	-			-1.42***
Log Likelihood		-96,040	-102,863	-91,315
Pseudo-R^2		0.08	0.02	0.13

Funding disruption risk represents a 25% or more decline in total revenues

Regression using the discrete hazard model with 280,698 firm-year observations and Huber-White standard errors to control for firm dependence.

Panel B: Classification Errors

	Tuckman & Chang	Altman	Ohlson	Naïve
% of False Failures	0.21%	0.02%	0.00%	0.00%
% of False Successes	98.26%	99.90%	99.97%	100.00%
% Correct Classification	87.49%	87.45%	87.45%	87.45%

Panel B uses 0.5 as the cut-off probability to classify the errors

Panel C: Relative Explanatory Power using Vuong (1989)

Comparison	z-statistic
Tuckman & Chang vs. Altman	10.5***
Tuckman & Chang vs. Ohlson	-9.6***
Altman vs.Ohlson	-70.6***
Tuckman & Chang and Altman vs. Ohlson	-9.6***

z-statistics resulting from Vuong Test (1989). Positive/(negative) values indicate that the first/(second) group of variables explains significantly more of the variance

All regressions include industry and year as controls (coefficients not shown)

*** (**) [*] significant at the 1% (5%) [10%] level (two-sided test)

TABLE 7
Program Disruption Risk

Panel A: Discrete Hazard Regressions

	Predicted Sign	Tuckman & Chang Model	Altman Model	Ohlson Model
Constant		-1.83***	-1.92***	-1.21***
NA/TR	-	0.00		
RCI	+	0.03		
NI/TR	-	-0.46***		
AE/TR	-	-0.46***		
WC/TA	-		0.01*	0.00
NA/TA	-		-0.01	
EBIT/TA	-		-0.02**	
TR/TA	-		0.00	
SIZE	-			-0.09***
TL/TA	+			0.00*
CL/CA	+			0.00
NI/TA	-			-0.01
FFO/TL	-			0.00
INTWO	+			0.20***
NAFail	+			-0.03
CHIN	-			0.35***
Log Likelihood		-84,439	-85,196	-83,864
Pseudo-R^2		0.02	0.01	0.02

Program disruption risk represents a 25% or more decline in program expenses
Regression using the discrete hazard model with 290,579 firm-year observations and Huber-White standard errors to control for firm dependence.

Panel B: Classification Errors

	Tuckman & Chang	Altman	Ohlson	Naïve
% of False Failures	0.04%	0.01%	0.00%	0.00%
% of False Successes	99.44%	99.95%	99.99%	100.00%
% Correct Classification	90.85%	90.83%	90.83%	90.83%

Panel B uses 0.5 as the cut-off probability to classify the errors

Panel C: Relative Explanatory Power using Vuong (1989)

Comparison	z-statistic
Tuckman & Chang vs. Altman	9.9***
Tuckman & Chang vs. Ohlson	-6.6***
Altman vs.Ohlson	-23.6***
Tuckman & Chang and Altman vs. Ohlson	-6.2***

z-statistics resulting from Vuong Test (1989). Positive/(negative) values indicate that the first/(second) group of variables explains significantly more of the variance

All regressions include industry and year as controls (coefficients not shown)
*** (**) [*] significant at the 1% (5%) [10%] level (two-sided test)

TABLE 8
Expanded Models

Panel A: Discrete Hazard Regressions

	Predicted Sign	Insolvency Risk	Financial Disruption Risk	Funding Disruption Risk	Program Disruption Risk
Constant		0.2	-0.42***	-2.09***	-0.88***
NA/TR	-	-0.03***	-0.04***	0.00***	0.00
RCI	+	0.50***	0.77***	-0.14***	-0.24***
NI/TR	-	-0.09***	-0.32***	1.69***	-0.32***
AE/TR	-	-0.05**	-0.12	0.48	-0.31***
WC/TA	-	0.05	0.00	-0.01**	0.00*
NA/TA	-	-3.98***	0.01*	0.00	-0.00*
EBIT/TA	-	-0.16**	-0.05	-0.05	-0.04*
TR/TA	-	0.00***	0.00	0.00*	0.00
SIZE	-	-0.45***	-0.33***	-0.00	-0.09***
CL/CA	+	0.00	0.00	0.00	0.00
NI/TA	+	0.15**	0.04	0.05	0.04*
FFO/TL	-	0.00	0.00	0.00	0.00***
INTWO	-	2.06***	0.98***	0.73***	0.15***
NAFail	+		1.20***	0.19***	0.10***
CHIN	-	-1.81***	-1.31***	-1.42***	0.32***
COMREV/TR	-	0.34***	-0.03	-1.08***	-0.65***
INV/TA	-	0.00	0.00***	-0.00***	-0.00***
Number of Observations		265,374	271,046	271,888	275,621
Log Likelihood		-14,282	-80,451	-85,260	-80,911
Pseudo-R^2		0.36	0.19	0.19	0.04

Based on discrete hazard model with Huber-White standard errors to control for firm dependence. Industry and year included as controls (coeffcients not sh

COMREV/TR is commercial revenues divided by total revenues INV/TA is investment portfolio divided by total assets

Panel B: Classification Errors for the Exanded Models

	Insolvency Risk	Financial Disruption Risk	Funding Disruption Risk	Program Disruption Risk
% of False Failures	0.01%	1.32%	0.40%	0.03%
% of False Successes	98.58%	93.19%	88.35%	99.53%
% Correct Classification	98.37%	87.70%	88.62%	90.90%

Panel B uses 0.5 as the cut-off probability to classify the errors

Panel C: Relative Explanatory Power using Vuong (1989)

Comparison of New Models to Best Performing Benchmark Models (Ohlson)	z-statistic
Insolvency Risk	4.7***
Financial Disruption Risk	11.3***
Funding Disruption Risk	7.5***
Program Disruption Risk	6.3***

z-statistics resulting from Vuong Test (1989). Positive/(negative) values indicate that the first/(second) group of variables explains significantly more of the variance

*** (**) [*] significant at the 1% (5%) [10%] level (two-sided test)