Revisiting the Prediction of Financial Vulnerability

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Whether or not a nonprofit organization is vulnerable to financial problems is a concern of all stakeholders of the organization. Recently, Greenlee and Trussel (2000) and Trussel and Greenlee (2001) expanded Tuckman and Chang's work (1991) to predict which organizations are financially vulnerable. This article extends the work of these authors by developing a model of financial vulnerability that includes four financial indicators, controls for the sector to which an organization belongs, and is based on a sample of over ninety-four thousand organizations. The model is useful as a screening, monitoring, and attention-getting device.

FINANCIAL vulnerability is an organization's susceptibility to financial problems. Whether or not a nonprofit organization is susceptible to financial problems is a concern of all stakeholders of the organization, because financial problems might not allow an organization to continue to meet its objectives and provide services. Over ten years ago, Tuckman and Chang (1991) wrote their seminal article on the financial vulnerability of nonprofit organizations, and they described financial ratios that might indicate a susceptibility to financial problems. Recently, Greenlee and Trussel (2000) and Trussel and Greenlee (2001) expanded Tuckman and Chang's work to predict which organizations are vulnerable to financial problems. These models are based on comparing an organization's financial profile to those organizations that are considered financially vulnerable. This article extends the work of these authors and develops an alternative model to predict which organizations are financially vulnerable. The model is based on a sample of over ninety-four thousand organizations, includes four financial indicators, and controls for the broad sectors to which the organizations belong.

An understanding of the relationship between financial indicators and financial vulnerability should be of interest to a variety of groups. These groups include government agencies setting policies and monitoring grants and contracts, auditors conducting analytical reviews and determining the scope of audits, managers and board members working on strategic planning, suppliers and other potential creditors setting credit terms, and potential donors allocating resources (Trussel and Greenlee, 2001).

The model for predicting financial vulnerability uses a methodology well known in the for-profit sector (Beaver, 1966; Altman, 1968; Zavgren, 1983; Jones, 1987) and more recently in the nonprofit sector (Greenlee and Trussel, 2000; Trussel and Greenlee, 2001). This methodology uses accounting data as indicators of financial vulnerability and tests the validity of the model on two samples of organizations.

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Previous Models of Financial Vulnerability in Nonprofit Organizations

Although researchers have developed several models to predict financial vulnerability in the for-profit sector, they have only a few for the nonprofit sector. The seminal work in defining financial vulnerability in the nonprofit sector was that of Tuckman and Chang (1991, p. 445), who defined a nonprofit organization as financially vulnerable if "it is likely to cut back its [program] service offerings immediately when it experiences a financial shock." Such shocks might include an economic downturn or the loss of a major donor. They developed a model that includes four indicators of financial vulnerability in nonprofit organizations:

- The *equity ratio* measures the relative amount of equity that an organization has.
- The *revenue concentration index* is a measure of the amount and variety of revenue sources that an organization has.
- The *administrative cost ratio* measures the percentage of revenues spent on administrative, as opposed to program, costs.
- The *surplus margin* measures the excess of revenues over expenses relative to revenues.

Tuckman and Chang (1991) studied a random sample of 4,730 nonprofit organizations that filed an annual Form 990 tax return with the Internal Revenue Service (IRS) in 1983. Nonprofits falling into the lowest quintile for all four variables were defined as being "severely at risk" of becoming financially vulnerable, and those with any one of the four variables in the bottom quintile were defined as "at risk" of becoming financially vulnerable (p. 451). Tuckman and Chang's empirical tests were descriptive, not predictive, in nature.

Greenlee and Trussel (2000) extended Tuckman and Chang's research by adapting the four financial indicators and using methodologies common in the for-profit sector to develop a model to predict the financial vulnerability of nonprofit organizations. They defined an organization as financially vulnerable if it reduced its expenditures on programs for three consecutive years. Using logistical regression (logit) analysis, they found a significant relationship between financial vulnerability and three of the four indicators: the revenue concentration index, the surplus margin, and the administrative cost ratio. Using these variables, they were able to predict correctly 65 percent of the financially vulnerable organizations and 58 percent of all organizations as financially vulnerable or not. Also, applying their model to another sample, they were able to predict the correct classification of 61 percent of the financially vulnerable organizations and 61 percent of all organizations.

Trussel and Greenlee (2001) expanded Greenlee and Trussel's model (2000) in several ways. First, they controlled for the sector to which the organization belongs. They classified the organizations into six broad sectors: arts, education, human services, public benefit, health care, and other. Second, they added size (total assets) as an additional financial indicator to control for a variety of variables typically correlated with size. Third, they defined a financially vulnerable organization as one that had a significant decrease in equity balances over a three-year period. Also employing logit, they found that their model of financial vulnerability was statistically significant, as were three of the five financial indicators: the debt ratio (a variation of the equity ratio), the surplus margin, and the size of the organization. Also, some of the sectors added significantly to the model.

I expand these previous studies by using slightly different financial indicators, controlling for ten broad sectors instead of six, and using a much larger database to select the sample for empirical testing. Also, I compare the model developed in the present study to those of Greenlee and Trussel (2000) and Trussel and Greenlee (2001).

The Empirical Study

This section describes the data and methodology that this study used to estimate and test a financial vulnerability prediction model. The discussion includes the specification of the econometric model, the selection of a set of independent variables, the sample selection, and estimation methods.

The Financial Vulnerability Prediction Model

Determining precisely when an organization becomes financially troubled is problematic because a decline in actual and reported financial condition likely occurs over time. Gilbert, Menon, and Schwartz (1990) defined a financially vulnerable proprietary organization as one that had cumulative net losses over a three-year period. Similarly, financial problems in a nonprofit organization are assumed to cause a reduction in net assets over time, which would manifest itself through a reduction in revenues or an increase in expenses. Trussel and Greenlee (2001) define an organization as financially vulnerable if it had an overall reduction in its fund balance during a consecutive three-year period. The present study uses a similar definition, except that an organization must have had more than a 20 percent decrease in its fund balance over three years to be classified as financially vulnerable. Using a significant decline in the fund balance over three years provides more assurance that those classified as financially vulnerable were indeed having financial difficulties.

The idea behind this classification of financially vulnerable organizations is to use accounting variables to determine the financial profile of organizations that are financially vulnerable versus those that are not. The accounting variables used to develop the financial profiles are similar to those indicators used by Tuckman and Chang (1991), Greenlee and Trussel (2000), and Trussel and Greenlee (2001): the debt ratio, the revenue concentration index, and the surplus margin. However, this study does not use the administrative cost ratio, as the database does not include the information necessary to compute this variable. In addition to these three indicators, this study also considers the size of the organization and the sector to which the organization belongs.

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Debt Ratio (DEBT). The *debt ratio* is a measure of the relative amount of debt that the organization uses to finance its programs and projects. It is measured as the ratio of total liabilities to total assets. Organizations with relatively large amounts of debt may be less able to finance new and continuing programs and projects than those with relatively small amounts of debt. The higher the debt ratio, the more vulnerable the organization is to financial problems.

Revenue Concentration Index (CONCEN). The *revenue concentration index* is a measure of the amount and variety of revenue sources that an organization has. Organizations with few revenue sources may be more vulnerable to financial problems than those with multiple revenue sources. An organization with multiple sources might be able to rely on alternative sources of revenues if one source is temporarily depleted. In other words, organizations receiving revenues from relatively fewer sources are more susceptible to financial problems. The index is constructed by summing the square of the percentage share that each of the organization's revenue sources represents to total revenue. If a charity receives all of its revenue from one source, its revenue concentration index will be one. Conversely, the index of a charity with multiple sources of revenue will approach zero.

Surplus Margin (MARGIN). Charities with a relatively low *surplus* (the excess of revenues over expenses) may be more vulnerable to financial problems than those with a relatively high surplus. That is, an organization with a high surplus may be able to operate with a reduced surplus rather than resorting to a reduction in its program services. Thus, the lower the surplus margin, the greater the financial vulnerability. This variable is measured as the ratio of revenues less expenses to total revenues.

Size (SIZE). Factors such as age, reputation, economies of scale related to costs, and the like are typically correlated with size (Ohlson, 1980; Tinkelman, 1999). Thus, smaller organizations may be more vulnerable to financial problems. Following Tinkelman (1999), size is measured as the natural log of total assets.

Sector ($SECTOR_j$). Macroeconomic factors may affect different sectors of nonprofit organizations differently. For example, some types of organizations may have a different reaction to inflation or recession than others and thus may be more or less prone to financial problems due to the sector to which the organization belongs. The National Taxonomy of Exempt Entities (NTEE) defines ten categories of charities; therefore, this study used dummy variables to control for the ten broad sectors.

This discussion leads to the identification of five potential indicators of financial vulnerability. Table 1 summarizes the five indicators and the variables they imply. The expected sign of each variable shows whether the financial vulnerability is hypothesized to increase or decrease with that variable.

Smaller organizations may be more vulnerable to financial problems

Data Collection and Measurement

Most previous empirical studies on nonprofit organizations (Greenlee and Trussel, 2000, for example) have used the IRS Statistics of Income database for choosing a sample. This database, developed by the National Center for Charitable Statistics (NCCS), includes roughly ten thousand organizations with assets over $10 million and a random sample of approximately two thousand smaller organizations. It is biased toward very large organizations. Therefore, I used a database that includes many more organizations, especially smaller ones.

The data for the present study came from the IRS Core Files database, also developed by the NCCS. The Core Files database, like the Statistics of Income database, is limited to nonprofit organizations that the Internal Revenue Code section 501(c)(3) (that is, charitable organizations) recognizes as tax-exempt. However, the Core

Table 1. Financial Vulnerability Indicators

Indicator	*Measure*	*Expected Sign*
Debt ratio (EQUITY)	$\frac{\text{Total liabilities}}{\text{Total assets}}$	+
Revenue concentration (CONCEN)[a]	$\sum\left(\frac{\text{Revenue}_j}{\text{Total revenues}}\right)^2$	+
Surplus margin (MARGIN)	$\frac{\text{Total revenues} - \text{Total expenses}}{\text{Total revenues}}$	−
Size (SIZE)	Natural log of total assets	−
Sector ($SECTOR_j$)	Dummy variable[b]	?

[a]Revenue_j is the revenue from source j.
[b]See Table 2 for a description of the sectors. The variable is measured as one if the organization is a member of sector j and as zero if it is not a member.

Files database includes all (approximately two hundred thousand) organizations that were required to file a Form 990 or Form 990-EZ and is therefore more representative of the population of charitable organizations in the United States. Excluded from the requirement to file are religious organizations and organizations with less than $25,000 in gross receipts (NCCS, 1998). The difference in the average size of the organizations between the two databases is striking. In Trussel and Greenlee's study (2001) based on the Statistics of Income data and a sample of approximately seven thousand organizations, the average total assets was over $15 million for financially vulnerable organizations and over $24 million for those not financially vulnerable. However, using the Core Files and a sample of over ninety-four thousand organizations, I find that the average total assets were only $268,740 and $477,443, respectively, for those that are considered to be financially vulnerable and those that are not.

Of the 94,002 charities, 17,112 (18 percent) of these are financially vulnerable, and 76,890 are not

Froelich and Knoepfle (1996) and Froelich, Knoepfle, and Pollak (2000) discuss the reliability of the IRS data and conclude that the Form 990 data are reliable for major categories of accounts, such as total revenues and total assets, but less reliable for some other accounts. All of the variables in this study, except for the revenue concentration index, are based on major categories of accounts. Also, the data were carefully screened for outliers (organizations that differ substantially from the sample).

To test the previous section's model, I compared a sample of charities that were financially vulnerable with a sample that were not. I defined a charity as financially vulnerable if it had more than a 20 percent reduction in net assets over a three-year period. Specifically, I consider an organization to be financially vulnerable if it had more than a 20 percent reduction in net assets over the 1997–1999 tax years. I considered no other organizations to be financially vulnerable. In order to develop a predictive model, I measured the variables using data from the 1996 tax year (that is, the tax year prior to the reductions in net assets).

The final sample consisted of the 94,002 charities. Based on the classification scheme I described, 17,112 (18 percent) of these are financially vulnerable, and 76,890 are not. Table 2 summarizes the sample by sector.

Empirical Results

In this section I provide the results of testing the model of financial vulnerability on a sample of charities that are not financially vulnerable.

Data Description

Table 3 presents descriptive statistics of the independent variables, partitioned by charities that are financially vulnerable and those that are not. As expected, financially vulnerable charities

Table 2. Composition of Sample

	Charitable Organizations	
	Number	*Percent*
Charities in database	228,004	100.0
Complete data not available	112,745	49.5
Outliers[a]	21,257	9.3
Final sample	94,002	41.2

Sector	*Financially Vulnerable*	*Not Financially Vulnerable*	*Total*
1. Arts, culture, and humanities	1,466	6,760	8,226
2. Education	1,767	10,843	12,610
3. Environment and animals[b]	399	2,106	2,505
4. Health	3,541	15,695	19,236
5. Human services	7,094	29,260	36,354
6. International, foreign affairs[b]	179	660	839
7. Public, societal benefit	1,704	7,686	9,390
8. Religion-related[b]	611	2,746	3,357
9. Mutual-membership benefit[b]	48	158	206
10. Unknown[b]	303	976	1,279
Total	17,112	76,890	94,002

[a]*Outliers* are defined as those charities with any financial indicator more than 1.5 hspreads above the seventy-fifth or below the twenty-fifth percentile of that indicator. An *hspread* is the length of the interquartile range. Because the data are not normally distributed, this method is used to identify outliers.
[b]Trussel and Greenlee (2001) combined these sectors into one "other" sector, because the Statistics of Income database includes very few organizations in these sectors.

Table 3. Descriptive Statistics for the Independent Variables

		DEBT	*CONCEN*	*MARGIN*	*SIZE*
Descriptive statistics and univariate tests					
FV	Mean	.4452	.7935	.1548	12.5015
	(SD)	(.3701)	(.1977)	(.0012)	(2.0716)
NFV	Mean	.3158	.7421	.1661	13.0762
	(SD)	(.2990)	(.2022)	(.0006)	(2.1727)
t-statistic		−48.873*	−30.234*	36.509*	31.554*
Wilcoxon	*z*-statistic	−42.731*	−30.661*	38.174*	32.524*
Pearson correlations					
CONCEN		.207*			
MARGIN		−.252*	−.125*		
SIZE		.098*	−.078*	.125*	

Note: The sample consists of 17,112 charities that are financially vulnerable (FV) and 76,890 charities that are not financially vulnerable (NFV). Table 1 defines the independent variables.
*Significance at the 0.01 level (two-tailed).

Have more debt (44.52 percent) than those that are not financially vulnerable (31.58 percent)
Have a higher concentration of revenues (0.7935) than those that are not financially vulnerable (0.7421)
Have a lower surplus margin (3.46 percent) than charities that are not financially vulnerable (8.52 percent)
Are smaller ($268,740 average total assets) than those that are not financially vulnerable ($477,443 average total assets)

Each of the differences is statistically significant.

The difficulty in predicting financial vulnerability is determining an appropriate cutoff probability for classifying organizations as financially vulnerable or not

Table 3 also provides a Pearson correlation matrix for the independent variables. The correlations between all of the pairs of variables are statistically significant. DEBT and MARGIN have the highest correlation (–0.252). The correlations appear within reasonable bounds and should not present a serious threat to the estimation of the logistic regression model.

Multivariate Model

In this section I empirically test this article's financial vulnerability model. Approximately half of the organizations in the sample were used to estimate a logit model, and the remaining organizations were used as a holdout sample. The significance of the model was addressed using logit, because the dependent variable is categorical (financially vulnerable or not) (Palepu, 1986; Maddala, 1991). Using this method, the underlying latent dependent variable is the actual probability of financial vulnerability. However, under logit the independent variable receives a value of one if the organization is financially vulnerable and of zero otherwise.

Table 4 includes the results of the tests. Overall, the model is statistically significant, indicating that the model fits the data well. Also, each of the independent variables is statistically significant with the expected sign. Each of the SECTOR dummy variables is statistically significant too.

Using the Model to Predict Financial Vulnerability

The computed value from the regression model (in Table 4) is the probability of financial vulnerability predicted for each organization. This probability can be used to predict the likelihood that an organization will become financially vulnerable. The difficulty in predicting financial vulnerability is determining an appropriate cutoff probability for classifying organizations as financially vulnerable or not. Jones (1987) suggests considering two important items in determining this cutoff probability: the cost of misclassification and the prior probability of financial vulnerability.

The first consideration in determining the appropriate cutoff probability for classification is the cost of misclassifying a financially vulnerable charity as not financially vulnerable (also known as a Type I error) or misclassifying a charity that is not financially

Table 4. Estimates of the Logit Model

Variable[a]	*Predicted Sign*	*Coefficient (SE)*	*p-value*[b]
Constant		0.2475 (0.2369)	0.2961
DEBT	+	1.1088 (0.0422)	0.0001
CONCEN	+	0.8402 (0.0716)	0.0001
MARGIN	−	−1.3527 (0.1022)	0.0001
SIZE	−	−0.1396 (0.0067)	0.0001
$SECTOR_1$	?	−0.8959 (0.2399)	0.0001
$SECTOR_2$	?	−0.9714 (0.2167)	0.0001
$SECTOR_3$	?	−1.2729 (0.2155)	0.0001
$SECTOR_4$	?	−0.9426 (0.2304)	0.0001
$SECTOR_5$	?	−0.8208 (0.2135)	0.0001
$SECTOR_6$	?	−0.9848 (0.2128)	0.0001
$SECTOR_7$	?	−0.8053 (0.2500)	0.0013
$SECTOR_8$	?	−0.9879 (0.2157)	0.0001
$SECTOR_9$	?	−1.1298 (0.2263)	0.0001
Model 1 Chi-square[c] 2,091.02 (p-value < 0.0001, two-tailed test)			

Note: The logit model is estimated using a sample of 7,161 charities that are financially vulnerable and 32,892 that are not.
[a]The latent dependent variable (FV) equals one if the charity is financially vulnerable and zero if the charity is not. Table 1 defines the independent variables.
[b]All p-values on coefficients are based on one-tailed t-tests, with the exception of the constant and SECTOR, which are based on two-tailed t-tests.
[c]Model Chi-square is the statistic of a Log-likelihood ratio test.

vulnerable as financially vulnerable (also known as a Type II error). The ratio of the cost of the two types of errors should be determined; however, the particular cost function is difficult to ascertain and will depend on the user of the information. For example, a creditor may want to minimize loan losses (and thus Type I errors); however, he or she will suffer an opportunity cost—the interest lost by granting the loan to another borrower at a lower rate (Type II error). In most cases the cost of a Type I error is likely to be much higher than that of a Type II error (Jones, 1987). Therefore, I incorporated several cost ratios into my analysis. Specifically, I included cutoff probabilities representing ratios of Type I to Type II errors of 1:1, 10:1, 20:1, 30:1, 40:1, 60:1, and 100:1.

The second consideration in determining the appropriate cutoff probability for classification is the prior probability of financial vulnerability. The *prior probability* is the actual percentage of financially vulnerable organizations in the population. If we use logit, the proportion of financially vulnerable organizations in the sample must be the same as the proportion in the population of all organizations to account for the prior probability, or else we must adjust the cutoff. This is normally a problem when one uses a paired sample method, which is not the case here. Because the proportion of financially vulnerable organizations in the population of all charities is not certain, I assumed that the proportion of financially vulnerable organizations in my initial sample, 0.18, is an unbiased estimator of the proportion in the population. Given the size of the sample (over ninety-four thousand organizations), this is a reasonable assumption. However, I also used alternative prior probabilities of 0.10 and 0.05.

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Table 5 reports the percentages of Type I errors, Type II errors, overall errors, and the expected cost of misclassification. Panel A reports the results based on a prior probability of financial vulnerability of 0.18. Panels B and C report the results based on prior probabilities of 0.10 and 0.05, respectively. The cutoff probabilities were chosen to minimize the expected cost of misclassification, which is the total cost of incorrectly classifying charities. This cost is computed by considering the relative cost of Type I and Type II errors, the percentages of Type I and Type II errors, and the prior probability of financial vulnerability (Beneish, 1999). To judge whether or not the model is cost effective, I compare these results to a naive strategy that classifies all charities as either financially vulnerable or not. If all charities are classified as not financially vulnerable, then there will be no Type II errors. Similarly, if all charities are classified as financially vulnerable, then there will be no Type I errors. Because the cost of the model relative to a naive strategy is less than one for most cases, the logit model is cost effective. I performed the same tests on a holdout sample of organizations. Because the results are similar to the initial sample, I do not report them.

Although the model is cost effective relative to a naive model, the error rates are still relatively high. Thus, the model should be used as a screening or monitoring device, with further investigation as to the classifications an important next step. This model is merely one possible way of measuring financial vulnerability in the nonprofit sector. Obviously, one should consider other financial and nonfinancial information when evaluating resource allocation and other similar decisions. Financial data are subject to inherent limitations, such as alternative accounting methods and discretionary accounting practices. Also, this model does not evaluate the effectiveness or quality of the organization's programs, as it focuses on financial condition.

Table 5. Predicted Classifications: Financially Vulnerable or Not Financially Vulnerable

Cutoff Probability[a]	*Relative Costs of Type I to Type II Errors (C_I:C_{II})*	*Type I Error Rate (P_I)*	*Type II Error Rate (P_{II})*	*Overall Error Rate*	*Expected Cost of Misclassification (Model)*[b]	*Expected Cost of Misclassification (Naive)*[c]	*Cost of Model Errors Relative to Naive Strategy*[d]
Panel A: Prior probability of FV = 0.18							
0.6600	1:1	1.0000	0.0000	0.1857	0.1800	0.1800	1.0000
0.0900	10:1	0.0504	0.8475	0.7005	0.7856	0.8200	0.9580
0.0400	20:1	0.0015	0.9868	0.8051	0.8145	0.8200	0.9932
0.0400	30:1	0.0015	0.9868	0.8051	0.8171	0.8200	0.9965
0.0400	40:1	0.0015	0.9868	0.8051	0.8198	0.8200	0.9997
0.0200	60:1	0.0000	0.9997	0.8154	0.8198	0.8200	0.9997
0.0200	100:1	0.0000	0.9997	0.8154	0.8198	0.8200	0.9997
Panel B: Prior probability of FV = 0.10							
0.6600	1:1	1.0000	0.0000	0.1844	0.1000	0.1000	1.0000
0.1600	10:1	0.3152	0.4656	0.4379	0.7343	1.0000	0.7343
0.0800	20:1	0.0322	0.8878	0.7300	0.8634	0.9000	0.9593
0.0600	30:1	0.0118	0.9486	0.7758	0.8890	0.9000	0.9878
0.0400	40:1	0.0015	0.9868	0.8051	0.8940	0.9000	0.9933
0.0400	60:1	0.0015	0.9868	0.8051	0.8969	0.9000	0.9966
0.0200	100:1	0.0000	0.9997	0.8154	0.8998	0.9000	0.9997
Panel C: Prior probability of FV = 0.05							
0.6600	1:1	1.0000	0.0000	0.1844	0.0500	0.0500	1.0000
0.6600	10:1	1.0000	0.0000	0.1844	0.5000	0.5000	1.0000
0.1600	20:1	0.3152	0.4656	0.4379	0.7576	1.0000	0.7576
0.1300	30:1	0.1739	0.6350	0.5499	0.8641	0.9500	0.9096
0.0900	40:1	0.0504	0.8475	0.7005	0.9058	0.9500	0.9535
0.0700	60:1	0.0202	0.9213	0.7551	0.9358	0.9500	0.9851
0.0400	100:1	0.0015	0.9868	0.8051	0.9448	0.9500	0.9945

[a]The cutoff probabilities were chosen in order to minimize the expected costs of misclassification.
[b]The expected costs of misclassification, *ECM,* were computed as $\text{ECM} = \text{P(FV)}P_I C_I + [1 - \text{P(FV)}]P_{II}C_{II}$, where P(FV) is the prior probability of financial vulnerability, P_I and P_{II} are the conditional probabilities of Type I and Type II errors, respectively. C_I and C_{II} are the costs of Type I and Type II errors, respectively.
[c]The ECM, based on a naive strategy of classifying all charities as not financially vulnerable is $\text{P(FV)}C_I$. The ECM based on a naive strategy of classifying all charities as financially vulnerable is $[1 - \text{P(FV)}]C_{II}$. The switch in strategy is at the point when the relative costs of Type I to Type II errors is greater than the prior probability of financial vulnerability.
[d]The cost of model errors relative to naive strategy is merely the expected costs of misclassification (model) divided by the expected costs of misclassification (naive).

Comparing the Models

In this section I compare the results of the model developed in this article to those of Trussel and Greenlee (2001) and Greenlee and Trussel (2000). As discussed earlier, both models are based on databases biased toward very large organizations. Exhibit 1 gives an

Exhibit 1. Computing the Financial Indicators

Revenue from source A:	$ 40,000	Administrative expenses:	$ 40,000
Revenue from source B:	$360,000	Total expenses:	$300,000
Total revenues:	$400,000	Total liabilities:	$250,000
Total assets:	$500,000	Total equity:	$250,000

Financial Indicator	*Formula*	*Example*	*Indicator Computed*
DEBT	$\frac{\text{Total liabilities}}{\text{Total assets}}$	$\frac{250{,}000}{500{,}000}$	0.500
CONCEN	$\sum\left(\frac{\text{Revenue}_j}{\text{Total revenues}}\right)^2$	$\left[\left(\frac{40{,}000}{400{,}000}\right)^2+\left(\frac{360{,}000}{400{,}000}\right)\right]^2$	0.8200
MARGIN	$\frac{\text{Revenues} - \text{expenses}}{\text{Revenues}}$	$\frac{400{,}000 - 300{,}000}{400{,}000}$	0.250
SIZE	ln(Total assets)	ln (500,000)	13.1224
EQUITY[a]	$\frac{\text{Total equity}}{\text{Total revenue}}$	$\frac{250{,}000}{400{,}000}$	0.625
ADMIN[a]	$\frac{\text{Administrative expenses}}{\text{Total revenues}}$	$\frac{40{,}000}{400{,}000}$	0.100

[a]These ratios are not needed for the present study, but they are needed for comparing to other studies (see Exhibit 2).

example of computing the financial indicators for the three models, and Exhibit 2 gives an example of computing the probability of financial vulnerability under each of the three models.

Under the present model, the computed probability is 0.1824, whereas the computed probabilities are 0.1112 and 0.0454 for the Trussel and Greenlee (2001) and Greenlee and Trussel (2000) models, respectively. The size of the organization and the sector to which the charity belongs play different roles in each of the models. The former model does not consider size and sector; the latter model is based on a sample biased toward very large organizations. Also, the former control for six sectors rather than ten sectors as the present model does.

Summary and Conclusion

Although researchers have used accounting information extensively in models predicting financial vulnerability in the for-profit sector, they have conducted little comparable research in the nonprofit sector. This study extends the models of Greenlee and Trussel (2000) and Trussel and Greenlee (2001) for predicting financial vulnerability by incorporating slightly different financial indicators, considering ten broad sectors of charities and using a much larger sample size.

The model assumes that a charity is financially vulnerable if it has more than a 20 percent reduction in its fund balance during

Exhibit 2. Comparing the Models of Financial Vulnerability

	Financial Indicators (A)	*Regression Coefficients*[a]			*Weighted Indicators*		
		Present (B)	*T&G (C)*	*G&T (D)*	*Present (A × B)*	*T&G (A × C)*	*G&T (A × D)*
Constant		0.2475	1.4398	−3.0610	0.2475	1.4398	−3.0610
MARGIN	0.2500	−1.3527	−5.2450	−3.4289	−0.3382	−1.3113	−0.8572
CONCEN	0.8200	0.8402	0.0764	1.2528	0.6890	0.0626	1.0273
SIZE	13.1224	−0.1396	−0.1594		−1.8319	−2.0917	0.0000
DEBT	0.5000	1.1080	0.9754		0.5540	0.4877	0.0000
EQUITY	0.6250			0.1153			0.0721
ADMIN	0.1000		0.1704	−2.2639		0.0170	−0.2264
Arts and culture	0	−0.8959	−0.7948		0	0	
Education	0	−0.9714	−0.9114		0	0	
Environment	0	−1.2729			0		
Health	0	−0.9426	−0.7220		0	0	
Human services	1	−0.8208	−0.6831		−0.8208	−0.6831	
Int'l or foreign affairs	0	−0.9848			0		
Public benefit	0	−0.8053	−1.0099		0	0	
Religion-based	0	−0.9879			0		
Mutual benefit	0	−0.1298			0		
Sum (Z)					−1.5004	−2.0789	−3.0453
Computed probability					0.1824	0.1112	0.0454

Assessing the Probability of Financial Vulnerability:
Step 1: Compute the financial indicators (see Exhibit 1).
Step 2: Compute the weighted financial indicators by multiplying the financial indicators by the regression coefficients.
Step 3: Determine Z by summing of all of the weighted financial indicators.
Step 4: Compute the probability using the following formula: $1/(1 + e^{-Z})$.

[a]The regression coefficients are based on the results from the present model (see Table 4), the Trussel and Greenlee model (2001) (T&G), and the Greenlee and Trussel model (2000) (G&T).

a three-year period. I use four financial indicators of financial vulnerability—the debt ratio, the revenue concentration index, the surplus margin, and the size of the organization—and control for the sector to which the organization belongs. I developed a predictive model using the methodology of Greenlee and Trussel (2000), and I found the model to be statistically significant. Within certain parameters, the model also proved to be cost effective relative to a naive strategy in determining whether or not a charity would become financially vulnerable.

Developing and testing the model revealed potential specification and measurement problems. I assume that a financially vulnerable charity is one that had more than a 20 percent reduction in equity over a three-year period. Also, in selecting my samples, I use a relatively short period (1996–1999) and limit my study to charitable organizations in the United States. Using alternative definitions of financial vulnerability, incorporating additional financial and nonfinancial variables, and extending the period of the study may improve the model. Finally, the data were selected from Form 990 information, which is subject to filing and data entry errors (Froelich, Knoepfle, and Pollak, 2000).

The model presented in this article can be used to predict the probability of the financial vulnerability of charitable organizations. It can be useful to government agencies determining contract, grant, and monitoring decisions; auditors developing an audit plan; potential creditors in determining the creditworthiness of tax-exempt organizations; and prospective donors deciding the amount and timing of contributions. The model is a useful screening, monitoring, and attention-getting device and should complement a rigorous financial analysis of an organization.

Although researchers have used accounting information extensively in models predicting financial vulnerability in the for-profit sector, they have conducted little comparable research in the nonprofit sector

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