The Survival of Nonprofits in the United States

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Abstract

The ability of publicly available tax information to determine the survival of nonprofit organizations is analyzed. Survival analysis estimates the predictive power and hazard ratios of several financial variables. The tax information comes from the National Center for Charitable Statistics (NCCS) 1998-2003 data on nonprofit organizations. The data includes 110,758 total organization and 1,857 failed organizations. The results show assets and return on assets had the greatest effect on survival time. The variables for equity ratio, months of spending, markup, and liquidity were not shown to have a clear and significant impact on survival time in nonprofits.

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L3

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Nonprofit Organizations
Nonprofit Finance
501(c)

A. Introduction and Review of the Literature

The nonprofit sector is a large and growing part of the United States economy. It contains over 1.4 million organizations that generate more than 1.8 trillion dollars a year in revenue. The nonprofit sector has grown 19.1 percent in number of organizations and 72.4 percent in revenue from 1999 to 2009 (Roeger, Blackwood, & Pettijohn, 2011). In spite of the importance of the nonprofit sector, it does not have a current literature on how the financial factors affect the survival or sustainability of nonprofits. This research paper goal is to determine if publicly available financial information can produce reliable prediction of nonprofit survival and sustainability.

In the for-profit sector the financial information on businesses is more detailed. The presence of stockholders and bond holders is a large reason for the greater amount of financial information. In the for-profit sector, the ability of publically available financial information to predict survival and sustainability has already been addressed in the academic literature (Goot, Giersbergen, & Botman, 2009; Hensler, Rutherford, & Springer, 1997; Jain & Kini, 1999; Lamberto & Rath, 2010). The size of a company and number of risk factors during an Initial Public Offering (IPO) were consistent in having a predictive power on survival. Operating cash flow over liabilities was also found to have predictive power in determining survival of a firm (Goot et al., 2009). Survival analysis, a.k.a. duration analysis, is the preferred method in the most recent literature on for-profit firm survival.

The primary source of nonprofit financial information for researchers is the 990 tax form information, which is digitized by the IRS (Arnsberger, Ludlum, & Riley, 2006). The National Center for Chartable Statistics (NCCS) created a dataset from the 990 tax form data. The dataset covers financial year 1998 to 2003, and it uses several methods to clean the data and correct the data. The methods used, appears to follow the recommendation presented by the IRS (Ludlum, 2004). The method recommended by the IRS produces the most accurate information available given the potential for errors.

The most recent literature on nonprofit financial terminology has proposed several useful terms (Bowman, 2011). These terms are easily derived from the 990 tax form information. The terms: return on assets (ROA), equity ratio (ER), mark up (MU), months of spending (MS), and liquidity are taken from this literature. The goal of this research paper was to determine if any of the terms mentioned can predict nonprofit firm survival.

A.1 Hypothesis's of the independent variables

The for-profit literature on survival has a style of listing a hypothesis for each regressor (Hensler et al., 1997; Jain & Kini, 1999; Lamberto & Rath, 2010). This style provides benefits to both researchers and non-academic readers. It provides a look into the logical assumptions of researchers. The formulas presented here are collected from the most recent literature on nonprofit finance (Bowman, 2011). The final model does contain each of the terms.

Log of Assets- The assets at the end of the year were transformed with the natural log. Organization with high levels of assets will likely be able to handle the lean times of an economic downturn. The hypothesis for the Log of Assets is a positive relationship on survival and thus a negative relationship on the hazard ratio.

$$Log\ of\ Assets = \ln\left(total\ assets\right)$$

Equity Ratio (ER)- is the fraction of assets that a nonprofit organization has debt free. An ER ratio of one would indicate that an organization has no debts, while an organization operating completely on borrowed assets is displayed with an ER of zero. The can be negative can could be interpreted as insolvency. The hypothesis for ER is it will have a positive relationship with the survival of a firm. The hazard ratio will be the inverse and have a negative relationship to the ER ratio. It is reasonable to assume that an organization with a higher level of debt is at increased risk of failure. It also takes revenue for debt repayment, instead of its potential use in organizational investments.

$$\text{Equity Ratio (ER)} = \frac{\text{Total assets-Total liabilities}}{\text{Total assets}}$$

Return on Assets (ROA)- is similar to return on investments in for-profit organizations. The current literature has the minimum level of 3.4% for the ROA of an organization set by the long-term rate of inflation(Bowman, 2011). The hypothesis for ROA is it will have a positive relationship with survival and thus a negative effect on the hazard ratio. This is based on the fact that most assets have both physical depreciation and maintenance costs, making the cost of replacing and/or maintaining an asset higher than it face value in the long run. This characteristic makes it impossible for an organization to replace or repair it currents assets if the ROA is too low.

$$\text{Return on Assets (ROA)} = 100\%* \frac{\text{Total revenue-Total expense}}{\text{Total assets}}$$

Months of Spending (MS)- is the number of months an organization could continue operating if all sources of revenue stopped. The Hypothesis for MS is it will have a positive relationship with survival and a negative relationship with the hazard ratio. It is logical to conclude, an organization with no months of spending could cause it serious harm, if a major source of funding was reduced or eliminated.

Months of spending (MS) $=12\ months * \frac{Unrestricted\ financial\ assets - Unsecured\ debt}{Spending\ on\ operations}$

Markup (MU)- This term is the operating surplus an organization has each year. It is an important issue for organizations with assets that have high maintenance costs (e.g. Museum pieces) or technological obsolescence (e.g. Hospital equipment). The hypothesis for MU is it will have a positive relationship with survival and a negative relationship with the hazard ratio.

Markup (MU) $=100\% * \frac{Change\ in\ unrestricted\ net\ assets + Depreciation}{Spending\ on\ operations}$

Log of Assets- The assets at the end of the year were transformed with the natural log. Organization with high levels of assets will likely be able to handle the lean times of an economic downturn. The hypothesis for the Log of Assets is a positive relationship on survival and thus a negative relationship on the hazard ratio.

$$Log\ of\ \ Assets = \ln\,(total\ assets)$$

Liquidity- An organization’s ability to invest in opportunities and avoid borrowing money for unexpected cost is affected by liquidity. The hypothesis for liquidity is it will have a positive relationship with the survival of a firm and a negative relationship with the hazard ratio.

Liquidity$=12\ months * \frac{Nonprofit\ current\ assets - Current\ liabilities - Temporarily\ restricted\ net\ assets}{Spending\ on\ operations}$

B. Data

The data collected was from the National Center for Charitable Statistics (NCCS). The dataset is called the National Nonprofit Research Database (NNRD a.k.a. "digitized data) and contains information from 1998 to 2003. The dataset includes all Form 990 and Form 990-EZ filed by 501(c)(3) organizations that are required to file a tax return. 338,863 individual Employer Identification Numbers (EINs) were present in the database. Organizations were removed to minimize the chance of incorrectly filed tax returns biasing the estimates. An organization was excluded if it filed a final tax return in more than one year, it filed a final tax return and change of address in the same year, it filed a final and initial tax return in the same year, an organization existed after a final tax return was submitted, and it filed an initial return in more than one year. These five exclusions were necessary to ensure correctly filed final and initial tax returns, and if an organization filed final tax returns and then exited the market.

Additional exclusions were necessary because of the method of analysis. The survival analysis required continuous data to calculate estimates. If an organization only has one observation from 1998 to 2003 it was excluded likewise if an organization filed a final tax return in 1998 or an initial tax return in 2003 it was excluded. The data has the accounting method listed as accrual, cash, or other. Cash accounting will account for revenues or expenses when the physical transaction takes place. In contrast, accrual accounting will account for revenues or expenses as soon as a bill is received or pledge is made to an organization. Two identical organizations could look very different financially if the accounting methods were different. Accrual accounting is more consistent across nonprofit organizations than the other methods, because of the Generally Accepted Accounting Principles (GAAP) (Bowman, Tuckman, & Young, 2011). The final dataset only contained organizations with accrual accounting listed for every year.

C. Methods and Statistical Model

Survival analysis, which is the main method of analysis, has several different model variations. The final model will be explained, along with the method used to determine the final model.

Survival analysis or Duration analysis can be done several ways. Non-parametrically, semi-parametrically, or parametrically are different methods used in survival analysis. The non-parametric model was used to analysis the shape of the hazard function, but with the small number of accounting periods it did not provide a smooth survival function to analyze in fine detail. The semi-parametric model was estimated, but was eliminated because it fit the data poorly. The parametric models will be the main model for estimation. It contains several Accelerated Failure Time (AFT) distributions that allows the hazard function be non-monotonically increasing at all points. An organization that exists during a recession is likely to start with high levels of risk, and then it would transition to lower levels of risk after the economy has recovered. A hazard model with a monotonic increasing constraint would not allow the organization to have a constant or decreasing hazard level after the recession. Furthermore, The literature on for-profit internet firms in the United States showed during 1996 to 2001 the parametric model with an (AFT) distribution was the best fit for the data, because of the AFT distributions ability to handle non-monotonic hazard ratios during a recession (van der Goot, van Giersbergen, & Botman, 2009).

The independence of the survival time is an important requirement of survival analysis, otherwise additional model assumptions have to be made. The data on nonprofit organizations is censored independently of the survival time and does not need any additional assumption to deal with the method of censoring (Kalbfleisch & Prentice, 2002). The fit of the different parametric distributions were each tested to determine the distribution that best fit the data.

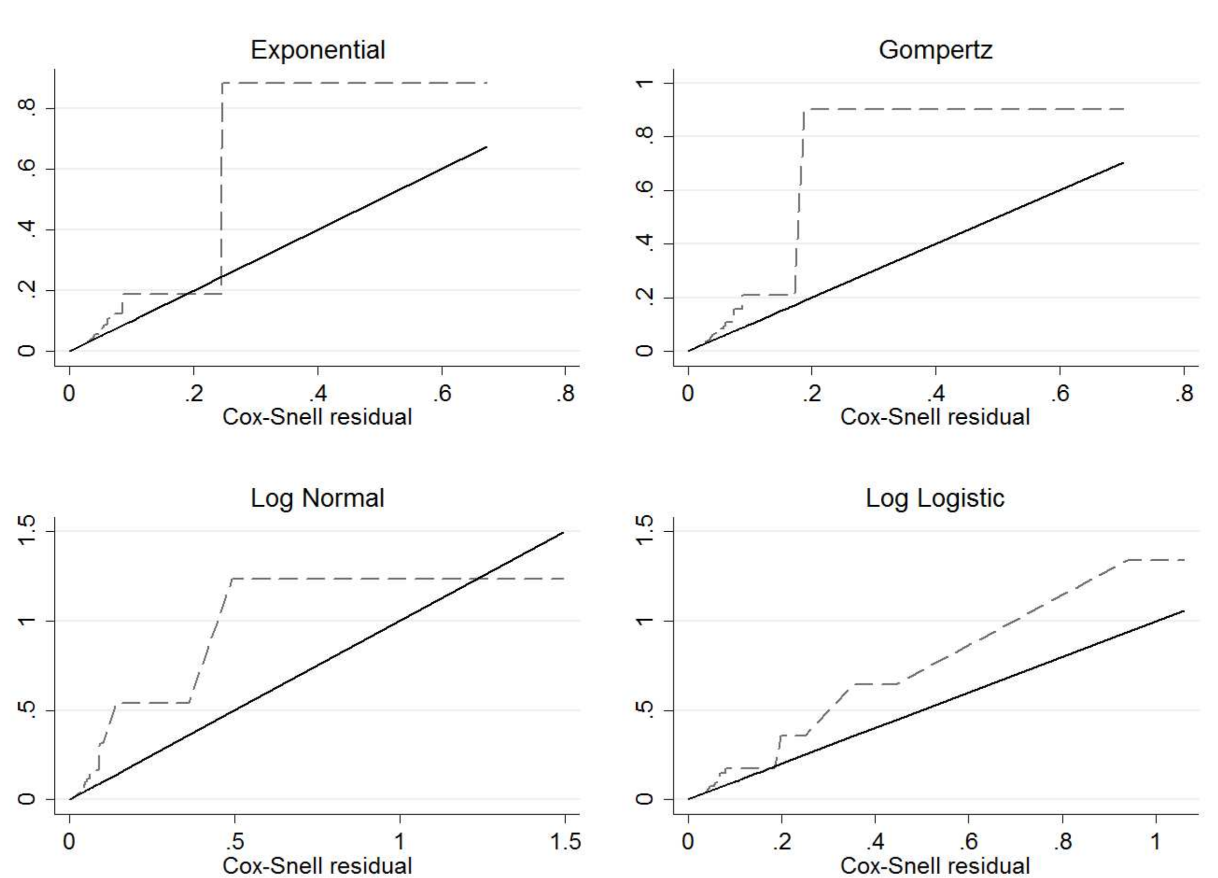
Table 1- Estimated Model Fit[1]

Type	Model	ll(null)	ll(model)	df	AIC	BIC
Parametric	Exponential	-5535.4	-5302.8	7	10619.6	10696.4
...	Weibull	-5474.2	-5240.8	8	10497.5	10585.3
...	Log-normal	-5470.6	-5256.1	8	10528.3	10616.1
...	Log-Logistic	-5474.4	-5240.4	8	10496.8	10584.6
...	Gompertz	-5479.2	-5245.2	8	10506.5	10594.3
Semi-parametric	CoxPH	-10093.6	-9860.1	6	19732.2	19798.1

1. Number of observations: 432845

Table 1 shows the Log-logistic model had the smallest AIC and BIC, which indicated it is the best fit among the models.

Figure 1-Cox-Snell Residual of Model Fit



In figure 1, the best fitting parametric models were graphed with their Cox-Snell residuals and cumulative hazard to visually judge model fit (Jones, Rice, d'Uva, & Balia, 2007). If the fit was perfect the dashed line would overlap the solid black line in the graphs. The Log-Logistic distribution was the best fit for the data and used to produce the final estimates.

$$\hat{h}(t_j|x_j) = \exp\left(-\beta_0 - \beta_1 lnassets_j - \beta_2 er_j - \beta_3 roa_j - \beta_4 ms_j - \beta_5 mu_j - \beta_6 lq_j\right) \quad (1.1)$$

The Log-Logistic model was then assigned a stratum. It is not uncommon for a large nonprofit organization to provide services to areas outside their zip code or state. The nine Census regions were chosen for the stratum[1]. This reduces the chance of a medium or large organization not having a single comparable organization in the same strata or region. There was concern of inter-cluster correlation within types of organizations (e.g. Health and Education). It is important to determine the possibility of a within group correlation, because it could bias the final estimates and overestimate the statistical significance of those estimates[2](Baum, Nichols, & Schaffer, 2010). The 13 major NTEE categories were used to estimate if an inter-cluster correlation existed for the financial variables used to produce the independent variables. The results showed strong indications of within cluster correlation for variables used to create the independent variables.

This result required the addition of a clustered and stratified estimation model to minimize the possible bias.

[1] This required removing US territories from the dataset. A list of the 9 stratas and 12 clusters is in appendix 3.

[2] The use of categorical or dummy variables would also produce biased estimates if the independent and identically distributed (i.i.d.) assumption is not met. The cluster method corrects for this (see Baum, Nichols et al. 2010)

Table 2-Final Model Fit

Model	Obs	ll(null)	ll(model)	df	AIC	BIC
Log-Logistic	432845	-5474.4	-5240.4	8	10496.8	10584.6
" with strata	422246	-5297.8	-4991.0	35	10051.9	10435.3
" with strata and cluster	422246	-5297.8	-5058.1	11	10138.2	10258.6

Table 2 shows the results from using the strata and strata with cluster versions of the Log-logistic model. The final model has a much better fit than the original Log-logistic model, but the difference between with strata and strata and cluster is mixed. The intraclass correlation was estimated to determine if clusters were needed. Several variables had an intraclass correlation large enough to require the use of clusters. Appendix 2 has a table of the interclass correlation for main variables.

The upper 1% of the distribution was removed. An quantile-quantile plot was used to determine the upper 1% was skewing the distribution. The results for the original, lower 99%, and middle 98% will be included in the results.

D. Results

The results for the original, lower 99 percent (L99), and middle 98 percent (M98) are presented in Table 2. The coefficients represent an acceleration of the baseline hazard with respect to time. If the coefficient is greater than one the survival time is reduced. If the coefficient is less than one the survival time is increased. A coefficient equal to one indicates no change in the baseline hazard.

Table 3-Final Log-Logistic Model

	Original	Lower 99 Percent (L99)	Middle 98 Percent (M98)
	coef.	coef.	coef.
lnassets	0.78922***	0.86596***	0.85703***
	(0.031654)	(0.017579)	(0.017168)
er	1.00039**	1.00031*	1.00027*
	(0.000197)	(0.000186)	(0.000827)
roa	0.98924***	0.99335***	0.99626***
	(3.05E-05)	(8.92E-06)	(1.32E-05)
ms	1.00000	1.00000***	1.00045**
	(1.86E-08)	(6.44E-07)	(2.07E-04)
mu	1.00000	0.99999***	0.99966*
	(1.97E-08)	(1.36E-06)	(1.84E-04)
lq	1.00000***	1.00000***	1.00000***
	(1.62E-09)	(6.88E-10)	(4.66E-10)
constant	0.10583	0.14416	0.15903

The variables for log of assets (lnassets), return on assets (roa), and liquidity (lq) were statistically significant at the one percent level for all groups. The results for lnassets had the expected direction with survival time increasing if assets increased. The variable for equity ratio (er) was statistically significant at the five percent level for the original group, and statistically significant at the ten percent level for the L99 and middle M98 group. The variable for months of spending was not statistically significant in the original group, but they were statistically significant for the L99 and M98 groups.

The effect of equity ratio (er) on the survival time was an inverse relationship. The survival time increases as the equity ratio decreases. This was not the expected direction for equity ratio, but the 95% confidence interval for equity ratio contained values in both directions. Indicating equity ratio does not have a clear effect on survival. This could indicate an organization improves survival by using available credit and maintaining a certain amount of debt. The effect of return on assets (roa) on survival time was a direct relationship. If return on assets increases the survival time increases. The markup (mu) and months of spending (ms) were very close to one in two of the three groups indicating they likely have no effect on survival time. The liquidity (lq) was equal to one for all three groups indicating it does not change survival time.

The interpretation of the coefficient of lnassets is an elasticity. A one percent increase in assets causes an increase in time till failure by 14.3 percent in the M98 group. A one unit change in the equity ratio produces a 0.027 percent decrease in the time till failure for the M98 group. Return on assets is in percentages, thus a one percent increase causes a 0.37 percent increase in the time till failure. A one unit increase in the months of spending causes a decrease in the time till failure by 0.045 percent for the M98 group. The months of spending small value, but it has a 95 percent confidence interval with only one direction, thus it is likely has a negative impact on survival. The coefficient for markup is in percentages, thus a one percent increase in markup causes a 0.034 percent increase in the time till failure. The 95 percent confidence interval for markup had values in both directions. Indicating it has no clear effect on survival time. Liquidity caused no significant change in time till failure.

It is important to understand the results are multiplicative for each year and not additive. For example, if an organization increased assets one percent each year for 4 years it will have increased the time till failure by 46.05 percent and not 57.19 percent. The results allow the estimation of the median and mean survival for nonprofits. The median length of survival for nonprofit firms was 36 years, and the mean length of survival was 46.51 years for the M(98) group.[3]

E. Discussion

The main purpose of this research paper was to find out if nonprofit's publically available tax information could produce predictable estimates of sustainability. The results show the publically available tax information has predictive power in estimating the sustainability of nonprofits. Incorrectly filled tax returns caused the greatest loss of data in the analysis. The original number of final tax returns was 18,842; and then, after cleaning 1,883 final returns were remaining. This left only 10 percent of the original amount of the final returns.

It will be important for the nonprofit community and the IRS to pursue sensible changes to the Form 990, which will clarify the terminology and do not alter a terms meaning from one year to the next. In a researcher's perfect world, the Form 990 would have a clear separation in the types of debt a nonprofit holds. Having information on the type of debt (e.g. bank loan, credit card, car loan) and available lines of credit would have been beneficial. It will be important for

[3] The results are estimated at the sample mean, and the shape parameter was used from the simple model without clusters.

future research in to take these issues into consideration. It will also be important to increase the amount of reliable nonprofit financial data.

In general, the amount of assets and return on assets produced consistent and meaningful changes in the survival time of nonprofits. The variables for equity ratio, months of spending, markup, and liquidity did not have a clear and significant impact on survival time in nonprofits. Months of spending and markup are considered short-term financial concerns, while return on assets and return on assets are long-term financial concerns[4].

Separating the twelve NTEE categories into individual estimates was not possible. The small amount of useable data prevented the estimation. It will be an important area of future research to produce estimates for each category. This will allow a greater understanding of the financial characteristics of individual nonprofit sectors.

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[4] Long-term financial variable include restricted assets. The reason for this is restricted assets are only realized in the long run.

Appendix 1

Summary Statistics

Original data after cleaning

	Total revenue	Total expenses	Total investment	Net assets end of year	ROA	ER	lq	MU	MS	lnassets
Mean	7.4189E+06	3.3100E+07	1.8609E+05	7.0010E+06	-4.2797E+04	1.2572E+05	3.4500E+07	-1.3608E+04	-2.5186E+04	1.3539E+01
Min	3.8000E+01	0.0000E+00	-3.7000E+07	-3.4000E+08	-4.6700E+09	-7.4600E+08	-2.0300E+10	-2.1000E+10	-1.7600E+09	0.0000E+00
Max	2.0000E+10	1.4900E+13	4.9200E+08	1.2000E+10	1.3600E+09	9.4800E+09	1.8400E+12	8.4600E+09	2.2200E+09	2.7406E+01
IQR*	2.1873E+06	2.0231E+06	2.2795E+04	1.5610E+06	1.7523E-01	5.6192E-01	9.1675E+06	1.4239E+01	8.8660E+00	2.8356E+00
SD	7.4300E+07	1.9700E+10	2.3760E+06	8.5600E+07	1.1400E+07	2.0200E+07	3.2600E+09	3.7000E+07	5.9146E+06	2.1929E+00

Lower 99% data after cleaning

	Total revenue	Total expenses	Total investment	Net assets end of year	ROA	ER	lq	MU	MS	lnassets
Mean	2.1628E+06	2.0719E+06	3.6596E+04	1.5583E+06	-7.9871E+03	3.2636E+04	8.1513E+06	-3.6296E+04	-2.5647E+04	1.3238E+01
Min	3.8000E+01	0.0000E+00	-4.6018E+06	-6.2300E+07	-2.8200E+08	-1.2400E+08	-4.6500E+08	-2.1000E+10	-1.6200E+09	0.0000E+00
Max	1.3400E+08	1.3800E+08	1.0700E+07	1.1900E+08	4.4800E+08	5.0700E+08	7.6000E+08	8.4600E+09	4.7100E+08	1.9207E+01
IQR*	1.5924E+06	1.4755E+06	1.6023E+04	1.1590E+06	1.8397E-01	5.5140E-01	6.7775E+06	1.3942E+01	8.6386E+00	2.6250E+00
SD	5.2710E+06	5.1856E+06	1.5496E+05	4.7289E+06	1.6154E+06	2.2705E+06	1.7900E+07	3.7500E+07	4.6309E+06	1.9111E+00

Middle 98% data after cleaning

	Total revenue	Total expenses	Total investment	Net assets end of year	ROA	ER	lq	MU	MS	lnassets
Mean	2.1112E+06	2.0054E+06	3.7146E+04	1.6663E+06	-2.4164E+03	2.4238E+04	8.2284E+06	2.6144E+04	-1.1368E+04	1.3284E+01
Min	2.5960E+04	1.3444E+04	-4.6018E+06	-2.3428E+06	-2.7000E+08	-1.2500E+07	-9.0922E+05	-7.0000E+07	-1.1300E+09	0.0000E+00
Max	1.3400E+08	1.3800E+08	1.0700E+07	1.1900E+08	9.0300E+07	5.0700E+08	6.5000E+08	4.1500E+09	3.0200E+08	1.9207E+01
IQR*	1.5748E+06	1.4503E+06	1.7033E+04	1.2362E+06	1.7727E-01	5.1883E-01	6.8857E+06	1.4229E+01	8.7892E+00	2.5495E+00
SD	5.0324E+06	4.8936E+06	1.5340E+05	4.7573E+06	7.1801E+05	2.0366E+06	1.7700E+07	8.4896E+06	2.4354E+06	1.8598E+00

Appendix 2

Intraclass correlation			
	Original	Lower 99%	Middle 98%
Total revenue	0.285	0.544	0.531
Total expenditures	0.000	0.549	0.535
Total investment	0.197	0.188	0.195
Net assets end of year	0.216	0.318	0.351

Appendix 3

Strata and cluster categories			
Strata		Clusters	
Census Regions		NTEE categories	
1	CT, ME, MA, NH, RI, VT	1	Arts, culture, and humanities
2	NJ, NY, PA	2	Higher education
3	IN, IL, MI, OH, WY	3	Education
4	IA, KS, MN, MO, NE, ND, SD	4	Hospitals
5	DE, DC, FL, GA, MD, NC, SC, VA, WV	5	Environment
6	AL, KY, MS, TN	6	Health
7	AR, LA, OK, TX	7	Human services
8	AZ, CO, ID, NM, MT, UT, NV, WY	8	International
9	AK, CA, HI, OR, WA	9	Mutual benefit
		10	Public and societal benefit
		11	Religion
		12	Unknown

Work Cited

Arnsberger, Paul, Ludlum, Melissa, & Riley, Margaret. (2006). *Current Research in the Nonprofit Sector*.

Baum, Christopher F, Nichols, Austin, & Schaffer, Mark E. (2010, July 2010). *Evaluating one-way and two-way cluster-robust covariance matrix estimates.* Paper presented at the Stata Conference, July 2010, Boston.

Bowman, Woods. (2011). *Finance fundementals for nonprofits:building capacity and sustainability* (1st ed.). Hoboken, New Jersey: John Wiley&Son, Inc.

Bowman, Woods, Tuckman, Howard P., & Young, Dennis R. (2011). Issues in Nonprofit Finance Research: Surplus, Endowment, and Endowment Portfolios. *Nonprofit and Voluntary Sector Quarterly, 41*(4), 1-20. doi: 10.1177/0899764011411925

Goot, Tjalling van der, Giersbergen, Noud van, & Botman, Michiel. (2009). What determines the survival of internet IPOs? *Applied Economics, 41*, 547-561.

Hensler, Douglas A., Rutherford, Ronald C., & Springer, Thomas M. (1997). The Survival of Initial Public Offerings in the Aftermarket. *The Journal of Financial Research, XX*, 93-110.

Jain, Bharat A., & Kini, Omesh. (1999). The Life Cycle of Initial Public Offering Firms. *Journal of Business Finance & Accounting, 26*(9), 1281-1307.

Jones, Andrew M., Rice, Nigel, d'Uva, Teresa Bago, & Balia, Silvia. (2007). *Applied Health Economics*: Routledge.

Kalbfleisch, J., & Prentice, R. (2002). *The Statistical Analysis of Failure Time Data* (2nd ed.). New York: John Wiley.

Lamberto, Andre Paul, & Rath, Subhrendu. (2010). The Survival of Initial Public Offerings in Australia. *The International Journal of Business and Finance Research, 4*(1), 133-147.

Ludlum, Melissa. (2004). *Data Interpretation across Sources: A Study of Form 990-PF Information Collected from Multiple Databases* Internal Revenue Service.

Roeger, Katie L., Blackwood, Amy, & Pettijohn, Sarah L. (2011). The Nonprofit Sector in Brief: Public Charities, Giving and Volunteering, 2011 (pp. 7): The Urban Institute.

van der Goot, Tjalling, van Giersbergen, Noud, & Botman, Michiel. (2009). What determines the survival of internet IPOs? *Applied Economics, 41*(5), 547-561. doi: 10.1080/00036840601007369