

Money Donations, Volunteering and Organizational Efficiency

JEFFREY L. CALLEN

Department of Accounting, Taxation and Business Law, Leonard Stern School of Business, NYU, Tisch Hall, 40 W. 4th St., Suite 400, New York, NY 10012-1118

Abstract

The purpose of this article is to explain the cross-sectional variation in money donations to charities at the organizational level. Using a unique data base which includes volunteer labor data, this article tests the hypotheses that money donations are positively related to volunteering and the technical efficiency of the firm. Technical efficiency is measured by a number of non-parametric indices. The empirical results indicate *inter alia* that the more technically efficient the charity, the more money donations it is able to raise. Moreover, at least for one model, money donations and volunteering are found to be complementary at the organizational level. In addition, the results in this article are not consistent with the well-known hypothesis that government financing crowds out private donations.

Key Words: nonprofits, volunteer labor, donations, efficiency

1. Introduction

The purpose of this article is to explain the cross-sectional variation in money donations to charities at the organizational level. Although the issue is not new [Steinberg (1986), Weisbrod and Dominguez (1986), Posnett and Sandler (1989)], previous empirical studies failed to include volunteer labor (donations of time rather than money) as one potential explanatory variable. This is not surprising since nonprofit institutions rarely publish quantitative volunteer labor data in their financial statements or in their annual report to the Internal Revenue Service (form 990). Nevertheless, at least one of these studies has noted the potential relevance of volunteering for explaining money donations at the organizational level.¹ Equally important, previous studies have not included organizational technical efficiency as a potential factor in explaining cross-sectional variations in money donations to nonprofits.² And yet, as evidenced by the recent rather sharp drop in donations to the United Way charities, technical inefficiency could have a dramatic impact on moneys donated to nonprofit organizations.³ Again, it is not surprising that previous studies have avoided the issue for the same reason they failed to include volunteer labor. Volunteer labor is an important input into the production of charity services. In the absence of this input, measures of the technical efficiency of charities are biased and meaningless.

In the process of explaining the cross-sectional variation in donations to charities, we hypothesize that money donations are complementary to volunteer labor at the organizational

level. This would be consistent with the empirical results of Clotfelter [1985] and Menchik and Weisbrod [1987] at the individual donor level. We also hypothesize that money donations and the technical efficiency of charities are positively related so that the more technically efficient charities are better able to attract money donations. In addition to explaining the cross-sectional variation of donations to charities, confirmation (nonrejection) of these hypotheses also implies that volunteer labor data are valuable at least to potential donors. Abstracting from the costs of collecting these data, this would imply, in turn, that mandating the publication of volunteer labor data in financial reports may be in the public interest.

2. The Economic Model

The empirical work to be presented below is based upon a model of public goods provision developed by Weisbrod and Dominguez [1986] and extended by Posnett and Sandler [1989]. They view nonprofit organizations in general and charities in particular as private organizations supplying public goods and services. The demand for these goods and services is not derived from the ultimate consumer in their models but rather from money donors. Donors are assumed to contribute money to nonprofit organizations that provide an implicitly agreed upon level and quality of public goods. Donors are further assumed to allocate personal resources among competing nonprofit organizations on the basis of *perceived* differences in price and quality of products supplied. In other words, the demand for public goods is not all that different from that of private goods except that it is determined by money donors rather than the ultimate consumers. Charities make their existence, and the services they provide, known to the public via fund raising activities, the equivalent of advertising. Donors then chose to *buy* these goods, that is, fund them, on the basis of price and quality.⁴ Donors may also respond to alternative sources of financing such as government funding, fees and investment income if they view charity output as primarily a nonrival pure public good so that what matters is the provision of the good rather than the specific source of financing. The elements of the model are, therefore, the private demand for public goods defined as money donations, the price of money donations, the quality of the goods, advertising, and other sources of financing. Each of these elements are now considered in turn.

The price of money donations (P) is defined to be the cost to the donor of increasing charity output by \$1. Specifically,

$$P = \frac{1}{1 - (f + a)} \quad (1)$$

where

f = proportion of total disbursements earmarked for fund raising⁵

a = proportion of total disbursements earmarked for administrative (and political) expenditures

For example, abstracting from tax effects, if fund-raising and administration are one quarter of total disbursements, donors will have to contribute \$1.33 to generate a \$1 increase in charitable output. On the other hand, if there are no fund-raising or administrative expenses, the opportunity cost of giving is at its lower bound of \$1. If the donations are tax deductible, equation (1) should be multiplied by one minus the donor's personal tax rate. Since there is no reason to assume that personal tax rates vary systematically across charities, both Weisbrod and Dominguez and Posnett and Sandler subsume the tax effect in the price coefficient.

Although charities do not advertise in the conventional sense, fund-raising makes potential donors aware of the charity's existence, the type and quality of services provided by the charity, and the social value of these services. Thus, fund-raising expenditures are equivalent to advertising expenditures in the private goods sector. Fund-raising, therefore, has two opposing effects on money donations. As an advertising proxy, it tends to increase the demand for money donations. On the other hand, fund-raising expenses drain resources from public goods provision, thereby increasing the price of the output, P , to donors and reducing money donations.

Money donors are also likely to respond to the quality of goods produced. However, since money donors do not directly consume the goods produced, they are not usually in a position to judge quality and must rely on the organization for quality information Hansmann [1980]. As argued by Weisbord and Dominguez, the institution's age since founding can serve as a proxy for its reputation and, hence, quality of services, absent more direct information about product or service quality.

Government financing, service fees, membership fees, and investment income represent alternative sources of funds to money donations. In the case of pure public goods, donors should only be concerned with the supply of these goods rather than specific sources of financing. Therefore, to the extent that there are other sources of financing, money donors are likely to reduce their contributions. In fact, this is a politically contentious and much researched empirical issue.⁶ Does government (and other sources of) financing *crowd-out* private money donations in the provision of public goods?

Both the Weisbrod and Dominguez study and the Posnett and Sandler study estimate similar demand functions, the former on U.S. data and the latter on U.K. data.⁷ Of the two, the Posnett and Sandler model is more comprehensive. The demand function for money donations facing the charity in the latter study takes the form:

$$\ln D = a_0 + a_1 \ln P + a_2 \ln F + a_3 AGE + a_4 \ln(F \times AGE) + a_5 \ln AUT + a_6 \ln G + u \quad (2)$$

where

D = money donations

P = price of public goods provision to money donors
as defined in Equation (1)

F = fund-raising expenditures

AGE = age of the institution since founding

AUT = autonomous income (e.g. fees, investment income)

G = government funding
 u = the usual white noise innovation term

The cross-product term $\ln(F \times AGE)$ reflects the interaction between age and fund-raising. This term would be negative, as argued by Weisbrod and Dominguez, if there are decreasing returns to fund-raising expenditures for older more reputable charities.

Like Weisbrod and Dominguez before them, Posnett and Sandler find the price, fund-raising, age and cross-product variables to be significant and of the appropriate signs by and large, depending upon the particular nonprofit industry in question. Specifically, they find the price coefficient to be negative, the fund-raising coefficient to be positive and the age coefficient to be positive as the model would predict. The alternative financing variables (missing in the Weisbrod and Dominguez study) were insignificant indicating that other sources of financing, including government financing, do not crowd-out private money donations.

The remainder of this article is devoted to empirically analyzing the effect of volunteering and organizational (technical) efficiency on money donations utilizing the empirical model of Weisbrod and Dominguez and its extension by Posnett and Sandler. In what follows, Section 3 describes the data. Section 4 briefly discusses the nonparametric technical efficiency measures used in this study. Section 5 provides the empirical results. Section 6 concludes the article. An appendix derives the nonparametric technical efficiency measure for nonsubstitutable output technologies.

3. The Data

Volunteer labor data at the organizational level are obviously crucial for implementing this study and yet such data are not readily available. Despite the American Institute of Certified Public Accountants auditing guidelines requiring valuation of donated services in financial statements, if an objective valuation basis is available, only on rare occasions do financial statements provide quantitative volunteer labor data. In the vast majority of cases, only a standard footnote vaguely alludes to the usage of volunteers. Even on those rare occasions when quantitative volunteer labor data are provided in financial statements, only the number of volunteers are reported—a not very informative piece of information—rather than volunteer hours. Although the IRS form 990, which nonprofits must fill out annually to maintain their tax-exempt status, asks for the value of donated services, the request is on a voluntary basis and is rarely provided. Fortunately, since 1986, Revenue Canada has requested quantity rather than dollar volunteer labor data from charities filing a Registered Charity of Information and Public Information Return (form T3010, the Canadian equivalent of the U.S. form 990), albeit also on a voluntary basis. Probably because the requested data are in quantity rather than value form, Revenue Canada is more successful than the IRS in eliciting the data. These fairly detailed returns also contain the remaining data pertinent to this study.

In order to measure technical efficiency at the organizational level, the sample must comprise an industry, that is, organizations in the sample must have reasonably similar inputs and outputs. *The 1988 Third Sector Donor's Guide to Fund Raising Organizations in Canada*

classifies charities into industry groupings. In order to have a meaningful sample, the largest such grouping, namely *Specific Health Focus Organizations* (including mental health) was chosen to be the subject of this study. In addition to being the largest charity type, this industry was chosen because the production technologies of the organizations within this group are fairly homogeneous and because these charities are pure nonprofits.

Of the 276 charities listed in this industry, 224 registered returns for the years 1986–1987 were obtained from Revenue Canada. Of these, 72 charities voluntarily provided volunteer labor data measured in annual volunteer hours employed. The specific diseases addressed by these 72 charities are: neurological (30), blindness (4), cancer (5), heart disease (4), social welfare (9), lung (8), mentally handicapped (6), and other (6).⁸ The fact that the volunteer labor data were provided on a voluntary basis raises the potential for selection bias; that is, voluntary disclosure may have been made by relatively more efficient charities. However, no specific analysis was made to determine the extent of selectivity, if any.

In order to measure the technical efficiency of an organization by nonparametric means, it is important to be able to specify and measure the organization's outputs and inputs. Our data source includes a section describing each organization's goals and activities. A careful cross-sectional analysis of this section yielded the output definitions. In particular, the primary goal of Specific Health Focus Charities is to raise funds from governmental and private sources in order to promote activities related to a specific disease. These activities are of two types: (i) transferring funds raised to researchers of the disease and to research institutions and (ii) disseminating information concerning the disease. For example, the Canadian Cancer Society raises funds for cancer research, and for disseminating information about cancer and cancer prevention via printed materials, meetings, lectures and advertising. Similarly, the Canadian Alzheimer's Society raises funds for researching Alzheimer's and disseminating information about the disease to those affected and the public at large via printed materials, meetings, and so on.

The above analysis of the Specific Health Focus Industry, mitigated by the available data, led us to define organizations in the industry as primarily fund raising institutions. Outputs were defined to be the total fund raised by the charity from (i) nongovernmental sources and (ii) governmental sources for the promotion of research and information dissemination activities. It is potentially important to distinguish between governmental and nongovernmental sources of funds because raising funds from governmental sources is likely to entail different input requirements than would nongovernmental sources. Access to governmental funding usually requires justification via documentation and specialized reports which may, in turn, require specialized remunerated labor expertise. On the other hand, nongovernmental funds are more readily tapped by personal connections, that is, by volunteer labor sources. In fact, it could well be that the technology for raising government funds is different from the technology for raising private funds. This possibility is addressed empirically in this study in the design of the nonparametric technical efficiency indices.

Our definition of charity outputs was dictated not only by conceptual analysis but also by data availability. A more exact and comprehensive output definition would most likely take into account the benefits provided to society by the research and information dissemination activities of the disease in question. Unfortunately, such a benefits measure of organizational output is not available and would, in any case, likely require fairly ad hoc assumptions about such factors as the value of basic research in disease prevention and control.

Therefore, we were constrained to measure charity output by the amount of funds raised by the charity rather than by the benefits these funds provide. Efficiency in this study refers to the efficiency of turning inputs into outputs, that is technical efficiency, rather than the effectiveness of the organization.

In addition to the data already mentioned, the Information Return for each charity includes a balance sheet and remuneration data for employees. (Most income statement data, however, are excluded from public purview by Revenue Canada.) The available data permitted us to specify three major inputs into charity fund-raising activities: (i) volunteer labor measured by the number of hours (per year) contributed to the charity; (ii) remunerated labor measured by total annual remuneration to all employees of the organization; (iii) and capital measured by the original cost of fixed assets (land, buildings and other fixed assets).

Except for volunteer labor, all other inputs are measured in dollar figures. This assumes that input prices are cross-sectionally constant (or at least approximately so) across different charities in the Specific Health Focus industry.

4. Measuring the Technical Efficiency of Charities

Measuring the technical efficiency of nonprofit organizations in general and charities in particular is bound to be difficult if only because the requisite data are hard to come by. Output price data are unattainable because charities do not normally charge for their services and even when they do, prices are heavily subsidized and do not reflect the true opportunity cost of services provided. Separate input prices are also largely unavailable. The nature of the data is important because it determines to a great extent the approach one uses to measure efficiency at the organizational (firm) level. Two methodologies are proposed by the literature for measuring efficiency. In the econometric approach, a stochastic production or cost frontier is estimated for the industry and each organization's (firm's) efficiency is assessed relative to the estimated frontier. A survey of this approach with references to the relevant literature is provided by Greene [1993]. Unfortunately, this methodology depends very much on having price data and, thus, is quite unsuitable for charities.

Data Envelopment Analysis (DEA), a non-parametric technique developed by Charnes, Cooper and Rhodes [1978] (hereinafter CCR), is the other extant methodology for measuring organizational-level technical efficiency.⁹ Although not an econometric technique, Banker [1993] shows that nonparametric DEA estimates maximize likelihood and are statistically consistent.¹⁰ DEA is admirably suited for measuring the technical efficiency of nonprofit organizations like charities because only input-output quantity data are necessary and explicit market prices need play no part in the analysis. DEA uses cross-sectional *ex post* input-output data of individual organizations in the same industry to map out the industry production function frontier. Unlike standard production theory, DEA does not presuppose a specific functional form for the industry production function. Rather, in CCR's original development, it is assumed that the industry production function can be approximated by piecewise linear functions.

The CCR technical efficiency index assumes that the industry production function exhibits constant returns to scale, a potentially severe limitation of the index. This led Banker,

Charnes and Cooper [1984] (hereinafter BCC) to generalize the original DEA model to allow for any degree of (local) scale economies. The BCC measure is identical to the CCR measure if, in fact, the technology does exhibit constant returns to scale for all production levels. Since we cannot know *a priori* if the organizations in our sample exhibit constant returns to scale, we present our results for both sets of technical efficiency indices.

Both the standard CCR and BCC indices assume that outputs and inputs are substitutable so that, for example, changes in production of one output will affect the production of other outputs. As argued above, however, charity outputs—funds raised from governmental and nongovernmental sources—may be generated by different technologies so that the outputs are not substitutable for each other. In this case the standard DEA indices may understate the degree of organizational inefficiency. Therefore, following Banker, Das, and Datar [1989], we also estimate CCR and BCC technical efficiency indices adjusted for the non-substitutability of outputs. The program for computing the latter indices is derived in an appendix.

5. Empirical Results

Table 1 lists sample means and standard deviations for selected data. More comprehensive summary statistics both for the 72 charities sample and the 152 charities in the Specific Health Focus field not reporting volunteer labor can be found in Callen and Falk (1993).¹¹

Table 1. Sample means and standard deviations of selected data (72 charities sample).

Variable	Mean	Standard Deviation
D	414	1,027
*P	1.68	1.50
L	27.1	92.3
F	75.6	155
AGE	24.9	19.4
AUT	157	337
G	114	475
EFF(crs-sub)	0.48	0.32
EFF(vrs-sub)	0.65	0.32
EFF(crs-non-sub)	0.39	0.30
EFF(vrs-non-sub)	0.54	0.33
COSTS/TOTAL RECEIPTS	0.29	0.29
D/TOTAL RECEIPTS	0.47	0.30

D = money donations (in \$000)	EFF = DEA efficiency index
P = price of donations (in \$)	crs = constant returns to scale
L = volunteer labor (in hours 000)	vrs = variable returns to scale
F = fund-raising expenditures (in \$000)	sub = substitutable technology
AGE = age of institution since founding	non-sub = nonsubstitutable technology
AUT = autonomous income (in \$000)	COSTS = F + administrative + political expenditures
G = government funding in (\$000)	

*Based on a sample size of 62

The price variable P is almost infinite for those organizations for which fundraising and administrative expenses are just covered by donations. This occurred in eight cases. Following Weisbrod and Dominguez, the price variable was truncated at $\ln p = 5$. The model was also estimated for lower and higher truncation values but the parameter estimates were insensitive to truncation values.

A number of the independent variables, especially fund-raising expenses took on zero values for some observations. To avoid taking the log of zero, we follow Posnett and Sandler in adding a constant (\$100) to all observations of these variables.

One major difference between the present study and those of Weisbrod and Dominguez and Posnett and Sandler is the large number of observations in the later studies and the concomitant aggregation of charity types.¹² Such aggregation would be fatal to our study since it would render meaningless our technical efficiency measures which presuppose a relatively homogeneous production technology. Nevertheless, since one purpose of this study is to see if the results of the two previous studies might be sensitive to volunteer labor and technical efficiency, it first behooves us to determine if our sample would yield results which are similar to these two other studies in the absence of volunteer labor and technical efficiency. If the results for our sample are sufficiently different, it could be argued that our sample is too small or too unique to represent the population of nonprofit institutions or even the population of charities.

Initially, we estimated Equation (2), the Posnett and Sandler demand equation, by ordinary least squares using our 72 charities sample. Like their regression, we found the price coefficient to be significant and negative while the government and autonomous financing variables were insignificant. Unlike Posnett and Sandler, however, we found the remaining variables, and most crucially the fund-raising variable to be insignificant. Given the smaller size of our sample and given the potential multicollinearity between the cross-product variable and its constituent components, that is, age and fund-raising expenses, it was decided to re-estimate the same regression after dropping the cross-product variable. This yielded the following regression equation:

$$\begin{aligned} \ln D = & 6.019^a - 0.302^b \ln P + 0.532^a \ln F + 0.008 \text{ AGE} \\ & (7.002) \quad (-2.115) \quad (7.937) \quad (1.397) \\ & + 0.054 \ln \text{AUT} - 0.008 \ln G \\ & (0.803) \quad (-0.140) \end{aligned} \quad (3)$$

$$R^2 = .6823 \quad \text{Adj. } R^2 = .6530 \quad F(6,65) = 23.27$$

^aSignificant at the 1% level

^bSignificant at the 5% level

The numbers in parentheses are t -statistics adjusted for White's [1980] consistent estimator of the covariance matrix allowing for possible heteroskedasticity.¹³

These results are far more consistent with those of Posnett and Sandler and Weisbrod and Dominguez so that in the regressions which follow we disregard the cross-product term. In particular, the price variable is negative and significant, the fund-raising variable is positive and highly significant and the government funding and autonomous income

variables are insignificant. Only the insignificance of the age variable is somewhat contrary to the Posnett and Sandler results since in their regressions this variable was significant by and large. When Posnett and Sandler disaggregated their data by industry, however, they also found the age variable to be insignificant in two of the four industries. The disaggregated samples are approximately the size of our sample. Also, the age variable may be noisy in that it does not always measure the true age of the institution but occasionally age since first obtaining tax exempt status from Revenue Canada.

Both the Posnett and Sandler and Weisbrod and Dominguez studies as well as the results just described find that the price coefficient is significant and negative. In a related study, Steinberg [1986] using a similar price variable but otherwise a different set of explanatory variables for money donations found the price coefficient to be insignificant. This he attributed, based on a robustness analysis, to the difference in functional forms which in his regressions is linear rather than log-linear. In order to evaluate the appropriateness of the log-linear functional form used in this study—as well as in the Posnett and Sandler and Weisbrod and Dominguez studies—a Ramsey Reset (2) test described in Godfrey, McAleer, and McKenzie [1988] was employed on our sample both for the linear and log-linear forms. The linear form unlike the log-linear form was rejected by our sample at the 5% significance level.

We hypothesized that money donations are positively related to both volunteering and the technical efficiency of the organization. To test these hypotheses, we re-estimated regression equation (2) with both volunteer labor and the technical efficiency index as independent variables. This approach assumes in particular that volunteer labor can be treated as an exogenous variable which is statistically independent of the error term in the regression. This would be the case if in contrast to money donations, for example, volunteering is *totally* determined by social, moral and/or religious values instead of economic factors. The empirical results using the substitutable output technology, variable returns to scale, DEA efficiency index (*EFF*) are as follows:

$$\begin{aligned} \ln D = & 5.955^a - 0.318^b \ln P + 0.362^a \ln F + 0.006 \text{ AGE} \\ & (5.866) \quad (-2.525) \quad (6.493) \quad (0.883) \\ & - 0.002 \ln \text{AUT} - 0.010 \ln G + 0.311^a \ln L + 0.320^a \ln \text{EFF} \quad (4) \\ & (-0.025) \quad (-0.254) \quad (2.888) \quad (6.954) \end{aligned}$$

$$R^2 = .7858 \text{ Adj. } R^2 = .7623 \quad F(7,64) = 35.94$$

^aSignificant at the 1% level ^bSignificant at the 5% level

The results for the nonsubstitutable output technologies, variable returns to scale, DEA efficiency index (not reported here) are qualitatively similar.

The two additional independent variables (*L* and *EFF*) neither affect the signs nor the significance of the other independent variables. Moreover, both of these new independent variables are statistically significant and in the hypothesized direction. As hypothesized, the more technically efficient the charity, the more the money donations it is able to attract—an elasticity estimate of over .3. Also, the more volunteer labor utilized by the charity, the more money donations it is able to attract—again an elasticity estimate of over .3—that

is, donations of money and donations of time are complementary to each other at the organizational level. Restricting the technology to constant returns to scale, the efficiency indices for both substitutable and nonsubstitutable technologies are no longer significant, although in all cases the volunteer labor coefficient remains significant and positive.

The previous regression assumed that volunteer labor is an exogenous variable. However, it is possible that volunteer labor is influenced by factors similar to those which affect money donations so that volunteer labor and the error term in equation (4) are contemporaneously correlated. Equation (4) was re-estimated using two-stage least squares. The instrumental variables to replace volunteer labor included the independent variables in equation (4) with the government funding variable measured by the proportion of government funding to total funding.¹⁴ This yielded the regression:

$$\begin{aligned} \ln D = & 4.844^a - 0.272^b \ln P + 0.158 \ln F + 0.003 \text{ AGE} \\ & (2.915) \quad (-2.086) \quad (0.918) \quad (0.305) \\ & - 0.101 \ln AUT + 0.811^b \ln L + 0.352^a \ln EFF \quad (5) \\ & (-0.895) \quad (2.330) \quad (4.331) \end{aligned}$$

$$R^2 = .6353 \text{ Adj. } R^2 = .6016 \quad F(6,65) = 94.14$$

^aSignificant at the 1% level ^bSignificant at the 5% level

Again, the volunteer labor variable is significant and positive signifying that money donations and volunteering are complementary at the organizational level. Also, as before, money donations increase significantly with the efficiency of the organization. Unlike the previous ordinary least squares regression, however, the fundraising variable is no longer significant.

An alternative approach to modelling money donations and volunteering, is to estimate the reduced form demand functions, one for public goods financed by donations of money and the other for public goods financed by donations of time.¹⁵ Although the opportunity cost of volunteer labor is a potential factor in influencing both demands, it is unlikely that the opportunity cost of volunteer labor varies cross-sectionally among Specific Health Focus charities. This parameter is therefore disregarded in the analysis.¹⁶

Employing the same log-linear form as before and estimating each equation by ordinary least squares yields the empirical demand functions:

$$\begin{aligned} \ln D = & 6.973^a - 0.358^b \ln P + 0.488^a \ln F + 0.007 \text{ AGE} \\ & (9.184) \quad (-2.544) \quad (7.867) \quad (1.207) \\ & + 0.070 \ln AUT - 0.052 \ln G + 0.318^a \ln EFF \quad (6) \\ & (1.098) \quad (-1.026) \quad (5.658) \end{aligned}$$

$$R^2 = .7298 \text{ Adj. } R^2 = .7049 \quad F(6,65) = 27.59$$

$$\begin{aligned} \ln L = & 3.275^a - 0.127 \ln P + 0.404^a \ln F + 0.003 \text{ AGE} \\ & (2.641) \quad (-0.763) \quad (4.212) \quad (0.354) \\ & + 0.232^b \ln AUT - 0.133 \ln G - 0.008 \ln EFF \quad (7) \\ & (2.118) \quad (-1.821) \quad (-0.074) \end{aligned}$$

$$R^2 = .4778 \quad \text{Adj. } R^2 = .4296 \quad F(6,65) = 10.87$$

^aSignificant at the 1% level ^bSignificant at the 5% level

The results for money donations are similar to those in Equation (3). When the DEA index is defined to be of the nonsubstitutable output technologies, variable returns to scale variety (not reported here), the EFF variable is no longer significant.

The volunteer labor regression yields a number of interesting results. First, donations of time appear to be positively related to fund-raising expenditures. This implies that volunteers are positively influenced by advertising to donate time to the institution. Second, volunteering is positively related to autonomous income. Thus, autonomous income would appear to facilitate (crowd-in) rather than crowd-out volunteering. Alternatively, this result may be due to the fact that autonomous income (comprising government financing, service fees, membership fees, and investment income) may be generated at least in part by the volunteers, e.g., service fees. Third, the substitutable output technology, variable returns to scale technical efficiency index is not significant implying that volunteers are indifferent to the technical efficiency of the organization. Using the other DEA measures, the technical efficiency index is significant but negative. This counter-intuitive result may simply be spurious, however, and due to the fact that volunteer labor is a production input and thus negatively related to DEA indices by construction. Fourth, the price variable is not significant implying that money donations and donations of time are independent of each other at the organizational level. Overall the volunteer labor regression implies that volunteer labor is far less affected by economic factors than are money donations. This may be because volunteering is primarily, but not totally, a function of social or religious pressures and issues such as technical efficiency are at best only of secondary importance to the volunteer.

In summary, the empirical results in this study imply on the whole that volunteer labor and technical organizational efficiency help to explain the cross-sectional variation in money donations. Whether donations of money are complementary to or independent of donations of time ultimately depends upon the particular assumed model.

6. Conclusion

At least for one model presented in this study, and at least for one nonprofit industry, volunteer labor would appear to be complementary to money donations at the organizational level. Like previous studies, we find no evidence that government funding crowds-out (or crowds-in) private donations. Perhaps, most interestingly, we conclude that money donations are affected by organizational efficiency. The more technically inefficient the organization, that is, the more it wastes resources, the less able it is to raise money donations.

Appendix: DEA Indices of Technical Efficiency for Nonsubstitutable Output Technologies

One crucial assumption underlying both the standard CCR and BCC DEA indices is that outputs (and inputs) are substitutable for each other. As emphasized in the text, however, charity outputs may not be substitutable for each other which means that standard technical efficiency indices overstate the degree of organizational inefficiency. Following Banker, Das and Datar [1989], we restate the standard DEA programs to allow for nonsubstitutable output technologies. Specifically, let $X_{ij}, Y_{rj} \geq 0$ represent input-output data for charity $j, j = 1, \dots, n$ where $i = 1, \dots, m$ is the index of the inputs and $r = 1, \dots, s$ is the index of the outputs. For each r (and organization o), we solve the extremal problem

$$\begin{aligned} \text{MINIMIZE} \quad & h_{ro} \\ & h_{ro}, h_{rj} \end{aligned}$$

SUBJECT TO:

$$- \sum_{j=1}^n h_{rj} X_{ij} + h_{ro} X_{io} \geq 0 \quad i = 1, \dots, m \quad r = 1, \dots, s$$

$$\sum_{j=1}^n h_{rj} Y_{rj} \geq Y_{ro} \quad r = 1, \dots, s$$

$$\sum_{j=1}^n h_{rj} = 1 \quad r = 1, \dots, s$$

$$h_{rj} \geq 0 \quad r = 1, \dots, s \quad j = 1, \dots, n$$

This yields s output efficiency indices for organization o . The aggregate technical efficiency index for this organization is computed as a weighted average of its output efficiency indices with the outputs as weights, that is: $(\sum_{r=1}^s h_{ro}^* Y_{ro}) / (\sum_{r=1}^s Y_{ro})$. This aggregate technical efficiency measure is the BCC technical efficiency index for nonsubstitutable output technologies.

The CCR aggregate technical efficiency index for nonsubstitutable output technologies is solved in a similar fashion after deleting constraints of the form $\sum_{j=1}^n h_{rj} = 1$ from the extremal problem.

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Notes

1. See, for example, Posnett and Sandler [1989, p. 199].
2. On the original definition of technical efficiency, see Farrell [1957].
3. On the alleged technical inefficiencies at United Way, see Shepard [1992].
4. For an alternative competing model, see Steinberg [1986]. On the empirical findings of Steinberg, see our comments in the text further below.
5. Disbursements include expenses as well as funds transferred to researchers and research institutions.
6. See the comments by Weisbrod and Dominguez [1986] on the Reagan Administration policies in this regard and the references cited therein.
7. Weisbrod and Dominguez use lagged independent variables to explain current money donations whereas Posnett and Sandler use contemporaneous independent variables. Although lagging the independent variables would appear to be conceptually preferable, this study follows Posnett and Sandler because our data set is comprised solely of contemporaneous data.
8. Neurological diseases include: cerebral palsy (8), alzheimer's (5), paraplegic (4), multiple sclerosis (4), epilepsy (2), Parkinson's (2), neuro-oncology (2), and other neurological (3). The others category includes: burns (2), drugs/alcohol (1), allergy (1), arthritis (1), and hemophilia (1).
9. The first attempt at a nonparametric approach to efficiency measurement was by Boles [1966]. For surveys of Data Envelopment Analysis, see Banker et al [1989], Seiford and Thrall [1990], Callen [1991], and Ali and Seiford [1993].
10. In the parametric approach to frontier estimation, including the programming formulations, maximum likelihood models have long been in use. See Schmidt [1985–86] and the references therein.
11. The Callen and Falk [1993] study used this same data base to investigate the relationship between organizational efficiency and the composition of the board of trustees of nonprofit institutions.
12. Weisbrod and Dominguez used a huge sample of 300,000 U.S. nonprofits categorized as being in the following industries: library, arts (exhibits, museums, zoo, etc.), goods and services to the poor and elderly, hospitals, aid to the handicapped, scientific research (diseases) and schools. Posnett and Sandler used a sample of 300 U.K. nonprofits categorized as being in the health, overseas, religious and social welfare industries.
13. We also looked for heteroskedasticity by graphing each of the independent variables against the model residuals. Heteroskedasticity is apparently not an issue in this study.
14. The proportion of government funding to total funding is highly correlated with volunteer labor hours and therefore serves as a more ideal instrumental variable.
15. This is analogous to standard demand theory with say two consumer goods in which the prices of the goods enter both demand functions. In general, an interior solution will obtain with both goods demanded. In particular, our formulation does not preclude the same good being financed by both money donations and donations of time.
16. Cross-sectional estimates of the opportunity cost of labor could not be obtained from the institutions in this study.

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