Quality, Service Level, or Empire: Which is the Objective of the Nonprofit Arts Manager?

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Abstract

In this paper, we examine the objectives of nonprofit arts managers. We approach this problem from both theoretical and empirical angles, building a structural model of arts nonprofit utility that distinguishes between the maximization of quality, the organization’s level of service, or its budget. We then construct an empirical method for testing which objective is evident in firm-level data. As an example application, we test the objectives of the managers of American public radio stations in the 1990s, finding that about half of stations have discernible objectives. The data show service is not an objective for about 30 percent of the stations; quality can be ruled out for 49 percent; and budget is rejected for 69 percent. In addition, large stations are harder to classify by objective than small ones are.
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Introduction

What is the objective of the nonprofit arts manager? It is convenient to assume a profit maximizing objective in the case of for-profit firms, but when the law prohibits the distribution of profits to firm owners, a more nuanced objective must be considered. For example, we might imagine that managers maximize their “output”: they seek to reach the maximum the number of clients, or service area. Alternatively, we might imagine that managers prefer to maximize quality, however measured. Perhaps more cynically, we might imagine that station managers are “empire builders,” seeking to maximize their budgets. Theoretically and empirically, these objectives present us with alternative hypotheses.

One of the most influential works on the economic objective of nonprofit firms is Steinberg (1986), who suggests that nonprofit “utility” would tend to fall along some continuum between service and budget size. The key in his formulation is fundraising expenditures; he calls organizations that maximize revenues net of fundraising expenditures “service maximizers,” while those that ignore expenditures “budget maximizers.” For Steinberg, the utility function of a nonprofit is a linear combination of these two possibilities. He finds that health nonprofits tend to be budget maximizers, while those in social welfare, education, and (most notably) the arts are service maximizers.
Steinberg’s formulation does not deal specifically with quality. However, especially in the case of arts and culture nonprofits, quality is an unavoidable consideration. Indeed, the prestige of, say, a symphony orchestra rests in no small part on the precision of its performances, and the prestige of a museum on the depth and value of its collection.

For arts nonprofits, Throsby (1994) and others note that “service” can refer to either quantity, (quality of service), or both. Hansmann (1981) distinguishes these as different maximands in his theoretic treatment of performing arts firms. He assumes that performing arts firms maximize utility with respect to audience size, quality, or budget. Luksetich and Lange (1995) test a simple version of Hansmann’s model in a study of American orchestras of different sizes in the 1970s and 80s. They find that, in general, large (in budget) orchestras are primarily quality maximizers and secondarily budget maximizers. In contrast, medium and small orchestras tend to be audience maximizers.

In this paper, we attempt to tackle the question of nonprofit managerial objectives, taking into account the quality “twist” that affects arts firms. We approach this problem both theoretically and empirically. We build a structural model of arts nonprofit utility, and test alternative hypotheses concerning the utility function. As an example, we test the objectives of the managers of American nonprofit “public” radio stations in the 1990s.

The rest of this article is organized in four parts. We begin with a discussion of the American nonprofit arts sector. We then develop a structural model of nonprofit arts managerial behavior that produces testable hypotheses. Following this, we introduce the public radio data that we use to test out hypotheses. The next section presents and discusses the empirical results. We close with conclusions and suggestions for future applications of our approach.
Dimensions of the American nonprofit arts sector

At two percent of the American nonprofit sector, the nonprofit arts represent an industry worth approximately $13 billion per year (Independent Sector 2001). Of this amount, 25 percent of activity is in the performing arts, 32 percent is in the visual arts and historic sites, and 43 percent is devoted to recreation and amusements (U.S. Census of Service Industries 1997).

Nonprofit arts organizations receive the bulk of their revenues from three sources: earned income, private donations, and government subsidies. For the average American nonprofit performing arts firm, 59 percent of income is earned, about 36 percent is donated, and about 5 percent comes directly from government (U.S. Census of Service Industries 1997). In 1997, Americans spent more than $10 billion on performing arts events, substantially more than on tickets to movies or sporting events (National Endowment for the Arts 1998). In some countries, the performing arts have an even higher proportion of earned revenues. In the late Soviet era, for example, musical organizations in the USSR (“nonprofits” by function, if not by legal definition) apparently earned upwards of 90 percent of their income at the box office (Rubinstein, et al. 1992).

Private charitable giving is substantial internationally, but especially large in the United States, where it amounted to $132 billion in 1997 (Independent Sector 2001). Approximately 70 percent of American households donated in 1998; 11.5 percent made contributions to the arts. The arts consistently represent less than 4 percent of household donations ($4.4 billion), but a much greater part of corporate and foundation
philanthropy. In 1997, private donations from all sources to the arts in the U.S. were about $10.6 billion (AAFRC 1998).

Public sector funding to the arts comes in two main varieties: direct and indirect. Direct subsidies are payments by governments to arts organizations. Indirect subsidies are taxes foregone on private contributions to these organizations. They result from tax laws that allow charitable donations to be deducted from taxable personal or corporate income before income taxes are calculated. Direct funding to the arts, at all levels of government, was about $623 million in 1998 (McCarthy, et al 2001). Indirect funding is estimated to be between three and five times this amount (Feld, et al. 1983).

**A model of nonprofit arts firm behavior**

We begin our analysis by defining $C$ as the arts firm’s client base and denote government subsidies by $G$ for a given firm. Levels of client base and government subsidies affect earned revenues $E(C, G)$: More potential consumers means more tickets sold, so $E_C \geq 0$. The sign on $E_G$ is indeterminant. Donations $D(F, C, G)$ are a function of fundraising investments $F$, as well as client base and the level of government subsidies. This relationship follows the common assumption in the literature that donations increase with the number of potential patrons and fundraising expenses (Rose-Ackerman 1982), but is agnostic on the role of subsidies, since past work has shown that government subsidies to the arts may either “crowd in” or “crowd out” private giving (Brooks 2000). That is, $D_C \geq 0$, $D_F \geq 0$, but $D_G$ is not determined. We assume that $E$ and $D$ are strictly concave in their arguments.
The amount of service $S$ is the real dollar value of resources devoted each period to producing the nonprofit’s product (as opposed to fundraising). Quality, $Q$, is measured by the level of service per consumer, or $S/C$. We assume output, fundraising expenditures, earned revenues, and donations are all nonnegative.

Profit, which we assume to be zero in each period, is

$$\pi = E(C,G) + D(F,C,G) + G - S - F = 0.$$  \(^1\)

This defines $S = E + D + G + F$.

We assume that arts nonprofits maximize a convex combination of quality, service, and budget. Utility is therefore given by

$$U = \alpha Q + \beta S + (1-\alpha-\beta)[E(C,G) + D(F,C,G) + G],$$

where $\alpha, \beta, \alpha + \beta \in [0,1]$. If stations are quality maximizers, $\alpha = 1$ and $\beta = 0$. For service maximizers, $\alpha = 0$ while $\beta = 1$. If they are budget maximizers, $\alpha = \beta = 0$.

Using the definition $Q = S/C$ and substituting equation (1) into (2), the firm’s problem can be stated as

$$\max_{c,F} \left\{ \alpha \frac{1}{C}(E + D + G - F) + \beta (E + D + G - F) + (1-\alpha-\beta)(E + D + G) \right\},$$

where all the variables are nonnegative. This yields the first-order conditions

$$\alpha \frac{1}{C}(E_c + D_c) - \alpha \frac{1}{C^2} S + \beta (E_c + D_c) + (1-\alpha-\beta)(E_c + D_c) = 0$$

$$\beta \frac{1}{C}(D_c - 1) + \beta (D_c - 1) + (1-\alpha-\beta)D_c = 0.$$  \(^4\)

\(^1\) This can be altered to hold intertemporally, with little loss of generality, to consider phenomena such as borrowing and endowments. An overlapping generations version of the structural model introduced here would represent interesting future research.
Equations (4a) and (4b) provide the conditions under which stations behave as quality, service, or budget maximizers. Note that the nonnegativity of $E_C$ and $D_C$ means that $E_C + D_C \geq 0$ for all levels of output. It involves straightforward algebra, therefore, to prove the following testable propositions:

1. If $E_C + D_C - S/C = 0$ and $D_F = 1$, the firm is a quality maximizer.
2. If $E_C + D_C = 0$ and $D_F = 1$, the firm is a service maximizer.
3. If $E_C + D_C = 0$ and $D_F = 0$, the firm is a budget maximizer.

These propositions represent testable hypotheses about an organization’s objectives.

The example of public radio

Moving to a concrete application of the model above, this section exposes the structural model from the last section to data on public radio stations from the 1990s.

“Public radio” is a misnomer, to the extent that it suggests government operates, or primarily funds, radio in the United States. The more than 600 public radio stations around the country are, as a rule, 501(c)(3) nonprofit organizations, classified as arts nonprofits by the Internal Revenue Service. Government, at all levels, covers an average of 33 percent of their funding (Brooks 2003). This is comparable with most other types of nonprofits (Independent Sector 2001).

These facts notwithstanding, government was indeed responsible for public radio’s birth. It was largely nonexistent until passage of the Public Broadcasting Act of 1967 (Engelman 1996). This Act grew out of the findings of the Carnegie Commission.

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2 In 1997, the nonprofit economy received 31.3 percent of its funding from the public sector in the form of direct subsidies. This figure does not include indirect subsidies (foregone taxes).
on Educational Television (1967), which argued that publicly-controlled media was integral to the social reforms of the time. The Act established the Corporation for Public Broadcasting (CPB), with an initial appropriation of $5 million for 1969 (about $24 million in year 2002 dollars). This quickly rose through the 1970s to over $300 million in today’s dollars; since then it has fluctuated around this level. While the CPB ushered in the era of public broadcasting, it subsequently came to constitute just one part of its funding. Indeed, today it is only 12 percent of total public broadcasting revenues.

Most of the limited economic literature on public radio has studied the objectives of donors and governments, as opposed to the stations themselves. Kingma’s 1989 study of the “crowding out hypothesis” finds that government funding, from the CPB and other sources, displaced private giving. Specifically, an extra $10,000 in total government money to a station crowded out about 15 cents from each individual donor. Kingma and McClelland (1995) broadly confirmed this result. Straub (2003), in considering the fundraising decision to be endogenous with the level of private donations, re-estimates the relationship and finds a statistically insignificant relationship between the variables. Brooks (2003) modeled the relationship nonlinearly, and found that low levels of government funding leveraged private giving, but displaced it at high levels.

To test hypotheses 1-3, this study employs an unbalanced panel of 104 public radio stations over the period 1990-96. The data were compiled from CPB records and initially analyzed by John Straub at the University of Wisconsin in 1999 (Straub 2000). They represent all nonprofit radio stations with assets of more than $10 million, as well as a probability sample of smaller stations.
The dataset includes information on private donations, earned revenues, government funding from various sources, expenditures on fundraising, listenership, and affiliations with NPR and/or a sister television station. We have augmented these data with state tax rates (Federation of Tax Administrators 2001) and per capita personal income (Statistical Abstract of the United States 2000), because both income and tax rates have been found to predict charitable giving (Steinberg 1993). Federal tax rates are not included, because all stations have listeners that are subject to the same rates.

Tables 1 and 2 describe the public radio data. After deleting firms for which the value of the population covariate is missing or for which there is a single valid observation (which would result in a zero-valued residual after controlling for the firm fixed effect), the data set consists of 395 observations for 95 firms. The definitions of the variables used in the analysis are presented in Table 1. Means for the entire sample as well as for two sample years are presented in Table 2. Approximately one percent of the total sample is from the year 1990, 15 percent is from 1991, 19 percent is from 1992, 20 percent is from 1993, 26 percent is from 1994, 28 percent is from 1995, and 2 percent is from 1996.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Donations ($D$)</td>
<td>Real annual donations ($ million)</td>
</tr>
<tr>
<td>Earned Income ($E$)</td>
<td>Real annual earned income ($ million)</td>
</tr>
<tr>
<td>Fundraising ($F$)</td>
<td>Real annual expenses on fundraising and development ($ million)</td>
</tr>
<tr>
<td>Government ($G$)</td>
<td>Real annual government funding ($ million)</td>
</tr>
<tr>
<td>Client Base ($C$)</td>
<td>Client base in listening area (millions)</td>
</tr>
<tr>
<td>NPR</td>
<td>Indicator for NPR affiliation</td>
</tr>
<tr>
<td>TV</td>
<td>Indicator for whether station has a sister television station</td>
</tr>
<tr>
<td>Personal Income</td>
<td>Personal income per capita in station’s metropolitan area or state ($10K)</td>
</tr>
<tr>
<td>Maximum Tax</td>
<td>Maximum tax rate for station’s state of incorporation (percent)</td>
</tr>
<tr>
<td>Service ($S$)</td>
<td>Real service spending ($ million)</td>
</tr>
<tr>
<td>Quality ($Q$)</td>
<td>Service divided by client base ($S / C$)</td>
</tr>
</tbody>
</table>
Econometric methods

The goal of our econometric estimation is to provide the coefficient estimates and covariance matrix necessary to test the quality, service, and budget maximization hypotheses. The null hypothesis of (expected) quality maximization is the joint hypothesis that 1) the marginal effect of fundraising on donations \( D_F \) equals one, and 2) the sum of the marginal effects of client base on donations and earned income...
\( (D_c + E_c) \) equals quality, defined as service per listener. Second, the null hypothesis of (expected) service maximization is the joint hypothesis that 1) the marginal effect of fundraising on donations equals one, and 2) the sum of the marginal effects of client base on donations and earned income equals zero. Third, the null hypothesis of (expected) budget maximization is the joint hypothesis that 1) the marginal effect of fundraising on donations equals zero, and 2) the sum of the marginal effects of client base on donations and earned income equals zero.

The choice of how to model donations behavior and the behavior of earned income is problematic. The data set of 86 firms spans the six years from 1991 to 1996. The shortness of the time dimension, therefore, makes it difficult to estimate autoregressive parameters for the disturbances. This problem is aggravated by the fact that the time series are interrupted—on average, there are less than four observations per firm and the observations for a firm are frequently nonconsecutive. These considerations led us to adopt the strategy of including firm fixed effects. We also experimented with calendar-year fixed effects and found them to have little explanatory power.

The functional form of the dependent variables relating to donations and earnings is also an important consideration. Adopting a semilog specification will reduce error dispersion when the behavior of firms of different sizes is being analyzed. Unfortunately, logging is not possible in the case of earnings, since it is possible, both theoretically and empirically, that earnings are negative—earnings range from $94 million to a loss of $1200 in the data. We therefore chose to leave earnings untransformed and to control for heteroskedasticity with the multiplicative model specification proposed by Harvey (1976). On the other hand, the semilog model is an appealing choice for donations. About
3 percent of the time, firms report zero annual donations. To adjust for this, we added the level of donations at the 4th percentile, about $1600, to each value of donations before logging.\(^3\)

Recall that we seek to estimate values of \(E_C, D_C\), and \(D_F\) in order to test hypotheses 1-3. The earnings equation can be modeled by:

\[
E_t = \alpha_i^e + X_i^e \beta^e + \varepsilon_i^e ,
\]

where \(i\) indexes the firms and \(t\) indexes calendar years. We assume that \(E(\varepsilon_i^e) = 0\), \(\text{var}(\varepsilon_i^e) = \exp(X_i^e \lambda^e)\), and \(\text{cov}(\varepsilon_i^e, \varepsilon_j^e) = 0\), for either \(i \neq j\) or \(t \neq s\). The parameter \(\alpha_i^e\) is the firm-specific fixed effect. The donations equation can be modeled by:

\[
\log(D_t) = \alpha_i^d + X_i^d \beta^d + \varepsilon_i^d .
\]

We assume that \(E(\varepsilon_i^d) = 0\), \(\text{var}(\varepsilon_i^d) = \sigma_i^2\), and \(\text{cov}(\varepsilon_i^d, \varepsilon_j^d) = 0\), for either \(i \neq j\) or \(t \neq s\).

While it is generally acknowledged that there is a positive relationship between donations and fundraising, the majority of papers assume that the relationship is one-way (fundraising affects donations, but not vice versa). Straub (2003), however, has argued that the variables are jointly determined. If the level of donations at any point in time during the year falls short of expectations, or the projected end-of-year level of donations falls short of expectations, fundraising will be increased. This makes it important to find an instrument for log fundraising in the log donations equation.

The only available choice is the lagged value of log fundraising. Even this is problematic since time series are interrupted and the lag of log fundraising is frequently

\(^3\) Fundraising is an important determinant of donations. We log fundraising as well as donations so that the fundraising coefficient can be determined as an elasticity. Firms report no fundraising somewhat more often (about 12 percent of the time) than no donations. This percentage may be as high as it is because of
missing. We therefore decided on the following strategy. We used two instruments, determined by the lagged value of log fundraising and the value of log fundraising lagged two years. The first instrument contains the lagged value of log fundraising when available, and equals zero otherwise. The second instrument is zero when the lagged value of log fundraising is available, and, otherwise, equals the value of log fundraising lagged two years. In the analysis below, we present both ordinary least squares (OLS) and instrumental variables (IV) results for the log donations equation.

The hypothesis tests concerning quality, service level, and budget maximization require an assumption about the contemporaneous correlation of disturbances across the donation and earnings equations. Extensive testing on the contemporaneous correlation of regression residuals suggests that the cross-equation correlation of disturbances is negligible.

Because the donations and earnings equation contain fixed effects, the values of the regressors are assumed to vary across \( t \) for a given \( i \), since otherwise, their coefficients will not be identified. However, some of the coefficient estimates needed for the hypothesis tests are for time-invariant variables. Hanushek (1974) has shown that it is possible to construct efficient estimators to recover the coefficients of the time-invariant variables using a two-step approach in which the estimated fixed effects are regressed on the time-invariant variables.

A more general version of the Hanushek approach has been used by Card and Krueger (1992, 1996) to examine how the quality of public schools in the respondent’s state interacts with the respondent’s years of education to determine his earnings. Card measurement error at low levels of fundraising. We added the level of fundraising at the 13th percentile, \$1750, to all fundraising values before logging.
and Krueger note that Hanushek two-step approach is asymptotically unbiased and efficient if the appropriate GLS estimation is used in the second step. Specifically, including the time-invariant variables in a single-step OLS estimation may yield biased or inefficient estimates in the presence of omitted time-invariant variables.

It seems easier to explain the Hanushek approach using matrix notation. In the present context, applying the Hanushek approach to the donations case, we have

\[
(7) \quad \alpha^d = Z\delta^d + \zeta^d,
\]

where \( \alpha^d \) is the \( n \times 1 \) vector of firm-specific fixed effects, \( Z \) is the \( n \times k \) matrix of time-invariant regressors, \( \delta^d \) is the \( k \times 1 \) coefficient vector, and \( \zeta^d \) is a mean-zero \( k \times 1 \) disturbance vector with variance matrix \( \sigma^2 I_n \). However, the true values of the fixed effects are not observed; only the estimated fixed effects, \( \hat{\alpha}^d = \alpha^d + \omega^d \), from the first step are observed. The vector \( \omega^d \), with variance matrix \( \Omega^d \), represents sampling error in the estimation of the fixed effects in the original equation.

The problem is to construct the efficient GLS estimator of \( \delta^d \) from the model:

\[
(8) \quad \hat{\alpha}^d = Z\delta^d + (\zeta^d + \omega^d).
\]

Assuming that \( \zeta^d \) and \( \omega^d \) are independent, the disturbance variance matrix is

\[
(9) \quad V(\zeta^d + \omega^d) = \Omega^d + \sigma^2 I.
\]

Since \( \Omega^d \) is known, feasible GLS estimation of \( \delta^d \) requires only an estimate for \( \sigma^2 \).

Hanushek derives the unbiased, consistent estimator

\[
(10) \quad \hat{\sigma}^2 = (s^2(n-k) - \text{diag}(\Omega^d) + \text{tr}(Z'Z)^{-1}Z'\Omega^d Z)/(n-k).
\]
The variance matrix of the combined coefficient vector \( \hat{\delta}^d \) can be calculated in a straightforward manner. If the variance matrix for \( \hat{\alpha}^d \) is written as

\[
V\left( \hat{\alpha}^d, \hat{\beta}^d \right) = \left( \begin{array}{cc} \Omega_{\alpha}^d & \Omega_{\alpha\beta}^d \\ \Omega_{\alpha\beta}^d' & \Omega_{\beta}^d \end{array} \right),
\]

the variance matrix for \( \hat{\delta}^d \) is given by

\[
V\left( \hat{\delta}^d, \hat{\beta}^d \right) = \Psi^d = \left( \begin{array}{cc} \Omega_{\delta}^d & A\Omega_{\alpha\beta}^d \\ A'\Omega_{\alpha\beta}^{d'} & \Omega_{\beta}^d \end{array} \right),
\]

where \( \Omega_{\delta}^d \) is the variance matrix of \( \hat{\delta}^d \), \( \Delta = \left( Z'W^{-1}Z \right)^{-1}Z'W^{-1} \), \( Z \) is the matrix of time-invariant regressors, and \( W^{-1} \) is the Hanushek weighting matrix. The corresponding variance matrix for the earnings coefficient estimates, \( \Psi^e \), is constructed in a similar manner. Assuming uncorrelatedness of disturbances across equations, the block-diagonal matrix \( \Psi \) with matrices \( \Psi^d \) and \( \Psi^e \) along the diagonal is the variance matrix for the full set of coefficient estimates. Since all the hypothesis tests that we perform are linear in coefficients, the matrix \( \Psi \) is the appropriate variance matrix for the Wald \( \chi^2(2) \) tests.

**Results and discussion**

The estimation results are presented in Table 3. Each estimation is divided into two “stages”. The stages do not refer to the stages of a two-stage least squares estimation or a feasible GLS estimation. Instead, no matter what estimation technique is used, OLS, IV, or GLS, the first-stage results represent the use of that technique for a model with
time-varying variables and firm-specific fixed effects. The estimates for the 86 fixed effects are not reported. The second-stage results represent the estimates of the Hanushek-efficient GLS estimation of the first-stage fixed effects on the time-invariant regressors.

Table 3. Coefficient Estimates For Donations and Earnings

<table>
<thead>
<tr>
<th>Time-Varying Variables</th>
<th>Log Donations OLS First Stage</th>
<th>Log Donations IV First Stage</th>
<th>Earnings GLS First Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log Fundraising</td>
<td>0.142 (0.066)</td>
<td>1.404 (0.644)</td>
<td>---</td>
</tr>
<tr>
<td>Government</td>
<td>-0.454 (0.220)</td>
<td>-0.561 (0.371)</td>
<td>-0.264 (0.144)</td>
</tr>
<tr>
<td>Squared Government</td>
<td>0.121 (0.024)</td>
<td>0.131 (0.040)</td>
<td>0.130 (0.030)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Time-Invariant Variables</th>
<th>Hanushek Second Stage</th>
<th>Hanushek Second Stage</th>
<th>Hanushek Second Stage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intercept</td>
<td>-0.833 (0.584)</td>
<td>0.990 (0.605)</td>
<td>-0.317 (2.292)</td>
</tr>
<tr>
<td>Client Base</td>
<td>0.437 (0.259)</td>
<td>0.075 (0.216)</td>
<td>0.764 (1.133)</td>
</tr>
<tr>
<td>Squared Client Base</td>
<td>-0.034 (0.017)</td>
<td>-0.017 (0.014)</td>
<td>-0.141 (0.075)</td>
</tr>
<tr>
<td>Client Base x NPR</td>
<td>0.047 (0.271)</td>
<td>0.115 (0.215)</td>
<td>1.227 (1.205)</td>
</tr>
<tr>
<td>Client x TV</td>
<td>-0.722 (0.280)</td>
<td>-0.674 (0.240)</td>
<td>8.311 (1.462)</td>
</tr>
<tr>
<td>NPR</td>
<td>-0.295 (0.461)</td>
<td>-0.660 (0.377)</td>
<td>-0.565 (2.031)</td>
</tr>
<tr>
<td>TV</td>
<td>1.910 (0.557)</td>
<td>0.995 (0.475)</td>
<td>-5.761 (2.419)</td>
</tr>
<tr>
<td>Maximum Tax</td>
<td>0.067 (0.156)</td>
<td>-0.005 (0.126)</td>
<td>-0.346 (0.687)</td>
</tr>
<tr>
<td>Squared Maximum Tax</td>
<td>-0.005 (0.016)</td>
<td>0.001 (0.013)</td>
<td>0.059 (0.071)</td>
</tr>
</tbody>
</table>

The results of the OLS and IV estimations of the log donations model are presented in the second and third columns of Table 3. Log donations are assumed to be
determined by the log fundraising and the level and the square of government funding. The OLS fundraising elasticity is 0.14. At the 5 percent level, it is both significantly positive and significantly less than one. When IV estimation is used, the estimated fundraising elasticity is 1.40, still significantly greater than zero, but now insignificantly different from unity. The instruments, constructed from the first and second-order lags of log fundraising as described above, work reasonably well in predicting fundraising. Their respective coefficients in an OLS estimation of log fundraising are 0.189 and 0.183 with p-values of 0.014 and 0.027. The $F_{2,200}$ statistic for joint significance of the instruments is 3.07, with a p-value of 0.049. The estimate of the fundraising elasticity of donations is needed to compute the derivative $D_F$. Letting $\beta_i^d$ represent the fundraising elasticity of donations,

$$D_F = \beta_i^d (D / F).$$

The GLS estimation results of the earnings regression to estimate the fixed effects (along with coefficients of the time-varying control variables, government funding and squared government funding) using Harvey’s (1976) multiplicative heteroscedasticity correction are presented in the third column of Table 3. One of the standard tests for the presence of heteroscedasticity is the Breusch-Pagan test (see Wooldridge, 2002, p. 127). In the case of multiplicative heteroscedasticity, the test statistic is formed from the $R^2$ of the regression of log squared OLS residuals on covariates hypothesized to explain the disturbance variance.

For this, we use time-varying covariates (government funding and squared government funding, but excluding log fundraising) and all time-invariant covariates (client base, squared client base, maximum tax rate, squared maximum tax rate,
indicators for NPR affiliation and the presence of a sister TV station, as well as the interaction of these indicators with client base), but do not include firm-specific fixed effects. The Breusch-Pagan statistic, $NR^2$, is distributed $\chi^2$ with degrees of freedom equal to the number of covariates (excluding the intercept). The value of the $\chi^2_{10}$ test statistic is 99.76, which is significant at the 1 percent level and suggests the presence of heteroscedasticity.

The second-stage Hanushek-efficient results yielding coefficient estimates for the time-invariant regressors are also presented in Table 3. The standard errors are computed from the corrected variance matrices $\Psi^d$ and $\Psi^e$. The time-invariant regressors consist of indicators for NPR affiliation and presence of a sister TV station, the levels and squares of the maximum tax rate and client base, and the interactions of client base with NPR affiliation and client base with the presence of a sister TV station.

Overall, the coefficients related to client base are not precisely estimated. The coefficient on the highest power, squared client base, is significant at the 5 percent level in the OLS donations case and at the 10 percent level in the earnings case. The effect of client base on donations is significantly smaller (at the 1 percent level) for firms with a TV affiliate. The opposite is true in the earnings case—the effect of client base on earnings increases for firms with a TV affiliate. This result is also significant at the 1 percent level.

The regression coefficients in Table 3 produce predicted values of the $E_c$, $D_c$, $D_F$, and $S/C$ for each individual firm. First, letting $\delta_i^d$ through $\delta_i^d$ represent the coefficients for the level and square of client base and the interaction of client base with
the presence of a sister TV station in the donations equation, the marginal effect of client base on donations is given by

\[ D_c = \delta_1^d + 2C\delta_2^d + \delta_3^d \times \text{NPR} + \delta_4^d \times \text{TV}. \]

Second, letting \( \delta_1^c \) through \( \delta_4^c \) represent the coefficients for the level and square of client base, the interaction of client base with NPR affiliation, and the interaction of client base with the presence of a sister TV station in the earnings equation, the marginal effect of earnings on donations is given by

\[ E_c = \delta_1^c + 2C\delta_2^c + \delta_3^c \times \text{NPR} + \delta_4^c \times \text{TV}. \]

The tests of hypotheses 1-3 yield results for each individual firm. Average marginal effects are calculated for each station, suing the values observed for all years reported in the data. There are, the proportions in Table 4 reflect only 86 observations (one per station). Table 4 summarizes results of the tests, listing the proportion of firms for which we can reject each possible objective

<table>
<thead>
<tr>
<th>Table 4. Hypothesis Test Results on Nonprofit Arts Objectives</th>
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<tr>
<td>All firms (N=86)</td>
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<tr>
<td>Large firms (N=43)</td>
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<td>Small firms (N=43)</td>
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</table>

\(^a\) 1 percent significance level used in tests

Among all the stations, the least prevalent outcome is rejection of the hypothesis that stations maximize service (30 percent reject). The most common finding is rejection
of the hypothesis of budget maximization (69 percent); quality maximization falls in between these two (49 percent). Therefore, we cannot rule out service maximization as a management strategy for most stations; although quality and budget cannot be excluded for many stations, either. The finding about quality is noteworthy because, while it is not treated systematically by authors in post studies, as defined here, it appears to be a fairly common objective.

In general, smaller stations (those with total annual revenues below the sample median) reject the three hypotheses less frequently than larger stations. This is especially true for service: while 49 percent of large stations reject this objective, only 12 percent of small firms do. The fact that large stations are so much more likely than small stations to have unclassifiable objections is somewhat perplexing. It may be that large stations tend to pursue a strategy apart from those identified here. Alternatively, large stations may in fact be less likely to have any coherent objective, particularly if they are pulled in different directions by their (presumably) large management teams. This incoherence would be consistent with research on nonprofit Boards of Directors, which has shown that particularly large boards tend to have trouble formulating firm strategy (Oster 1995). If this is the case it bolsters the familiar argument in the nonprofit management literature that many organizations are not firmly anchored, and performance standards can be useful for focusing nonprofit managers on desirable ends (Light 2002).

Conclusions

In this paper, we have introduced a model of nonprofit arts firm objectives which yielded testable hypotheses. Then, we described appropriate econometric methods for
performing these tests, using public radio data in an example application. We found that radio stations differ somewhat depending on size, but that in most cases, we cannot rule out service as a primary objective.

Our methods in this paper are certainly not specific only to public radio stations; which we used only as an example application our models could be used in a number of other contexts. Specifically, they require that an arts nonprofit (or nonarts firm, for that matter) be able to distinguish its customer population from the public at large. This may be difficult in the case of, say, a nonprofit dedicated to historic preservation. However, it would be ideally-suited to cases in which customers are clearly identifiable, such as is the case for the performing arts.
References


